Integrated AI-EM Approach for Modeling Components of AEPS

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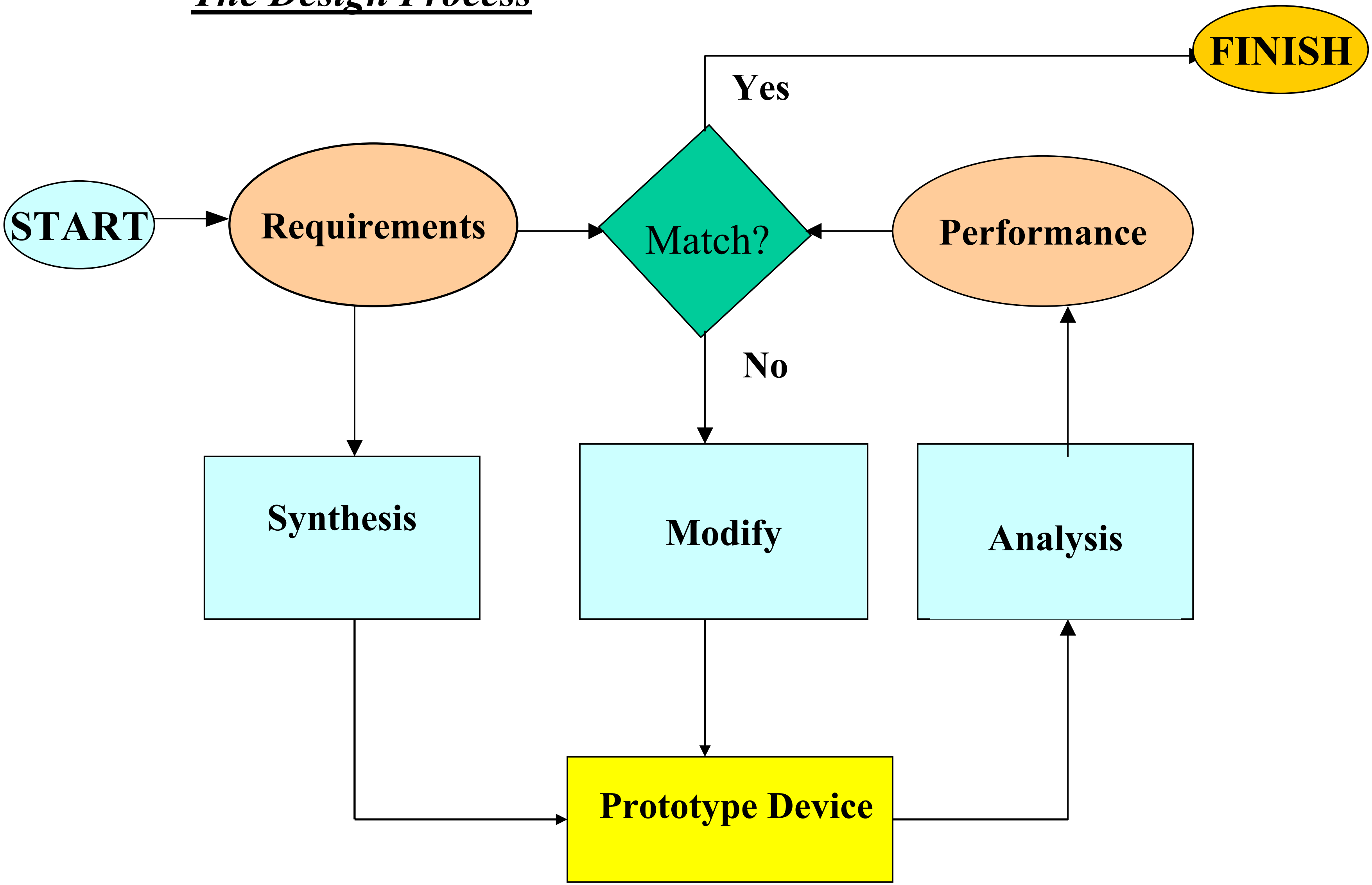
- *Artificial Intelligence (AI) is used in conjunction with computational electromagnetics to develop a modeling environment suitable for the "accurate" and "quick" characterization of high energy - high density advanced electric power systems applications.*

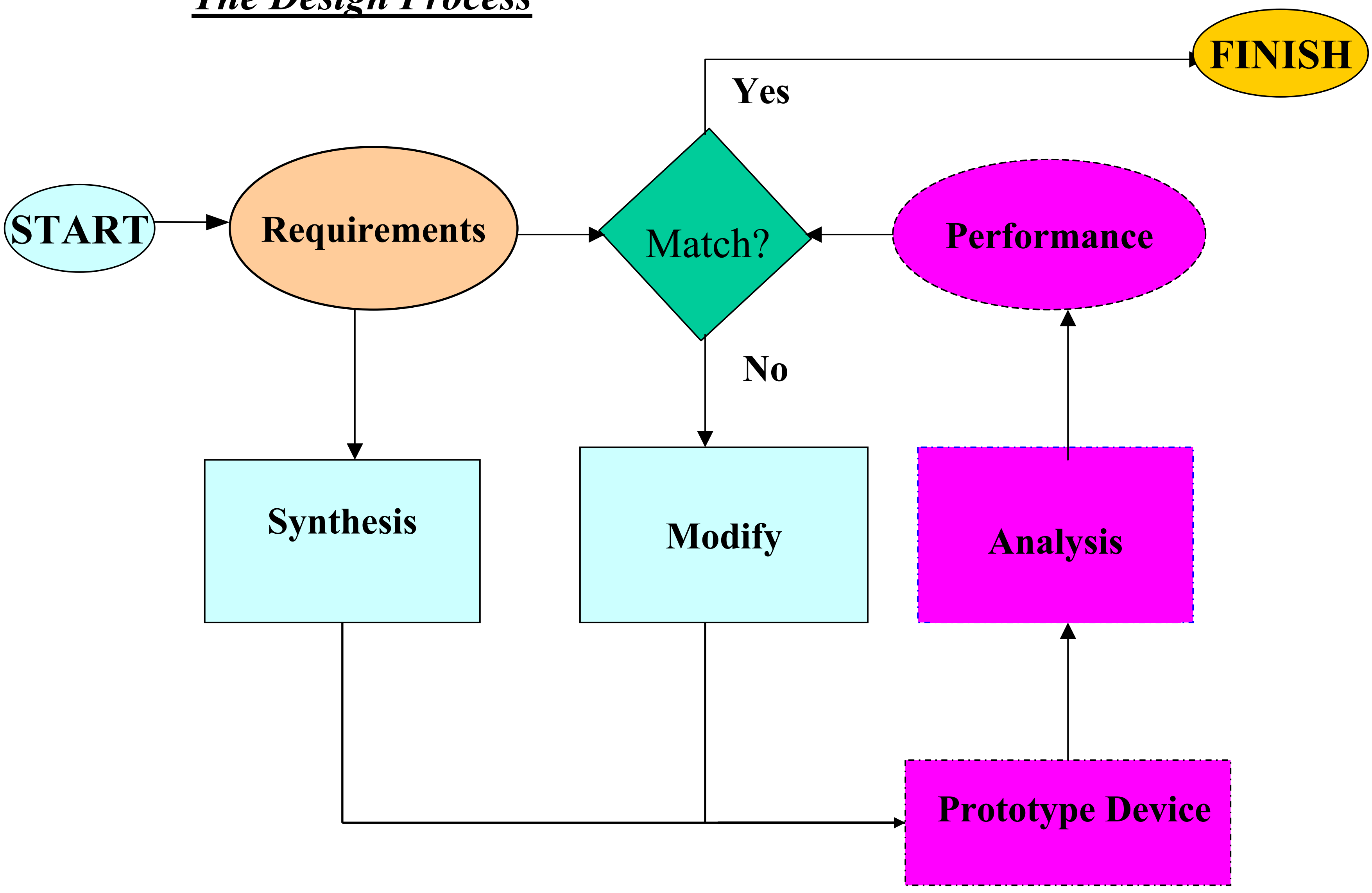
- *The integrated AI-Electromagnetic models can be used as well to model components in the Virtual Test Bed.*

- In this phase of the work, the modeling environment is used to perform the following tasks:
  - Conduct a comparison between two AI techniques, namely Artificial Neural Networks ANN and Fuzzy Logic (FL) based models as applied to a motor drive.
  - Develop AI-Electromagnetic models for the following systems:
    - Electromagnetic Actuators
    - Electromagnetic Launchers

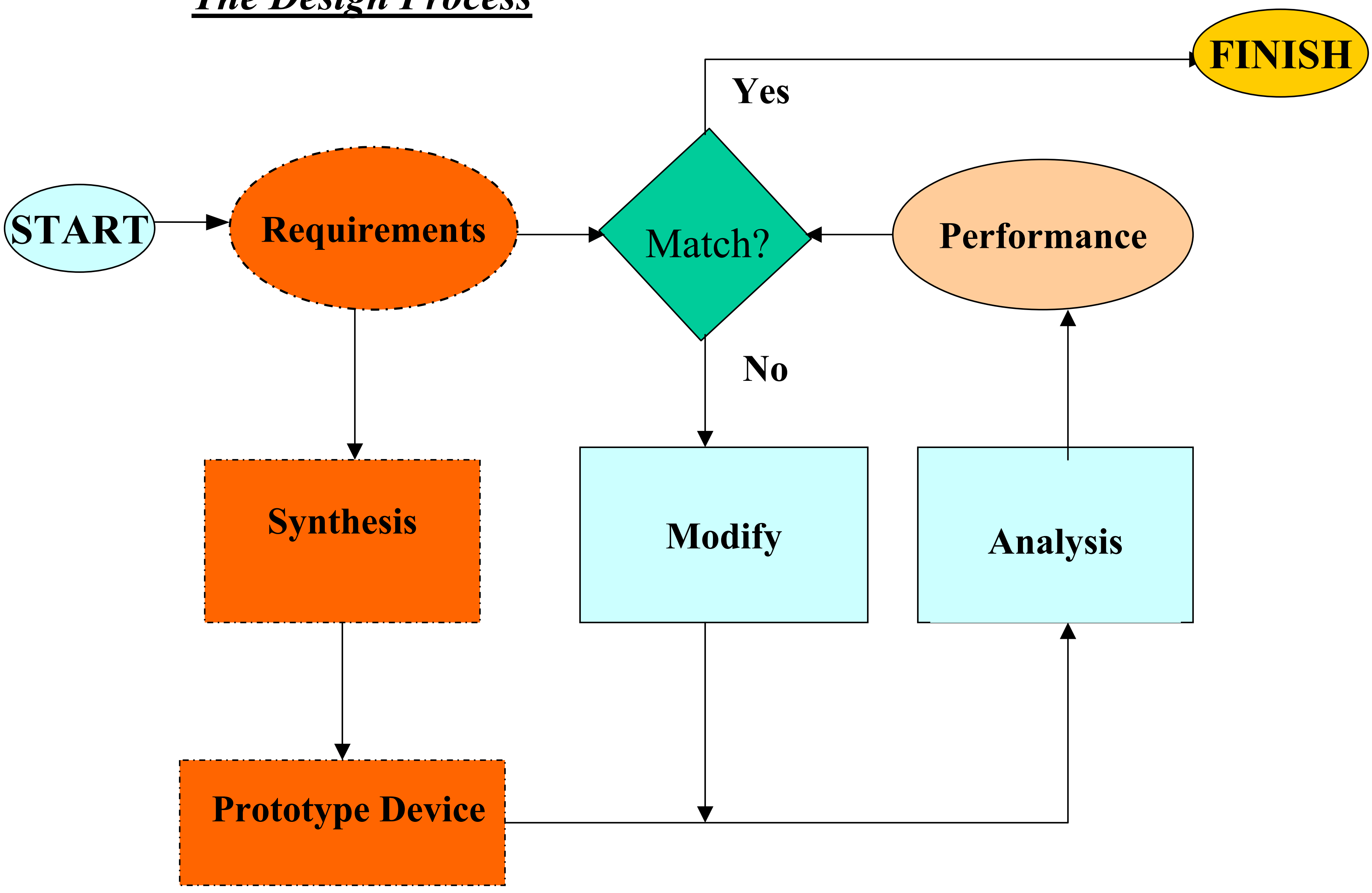
The Design Process



The Design Process



The Design Process



Direct Problem vs. Inverse Problem

Direct Problem

Inverse Problem

Characteristics of Inverse & Direct Problems

Direct problem:

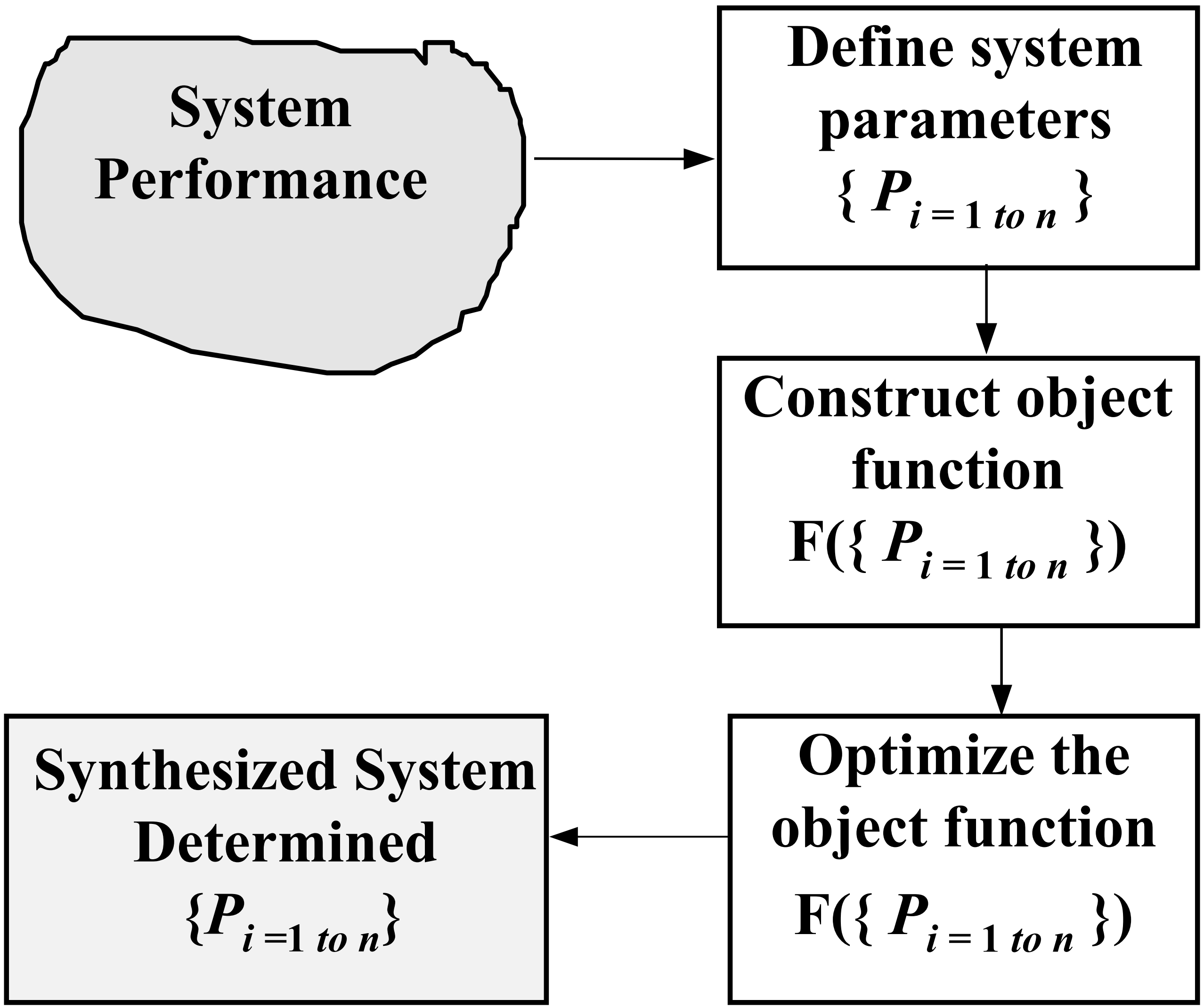
It is well posed

- existence : a solution exists
- unique : one solution
- stability : solution depends continuously on data

Inverse Problem:

– usually less is known about the problem
– ill posed

Solution Steps in Inverse Problem Methodology



Optimization Methods

- **gradient schemes or deterministic methods**
- **evolution strategies (ESs)**
- **artificial neural networks (ANNs)**
- **stochastic methods**
- **simulated annealing**
- **hybrid techniques**
- ***genetic algorithms (GAs)***

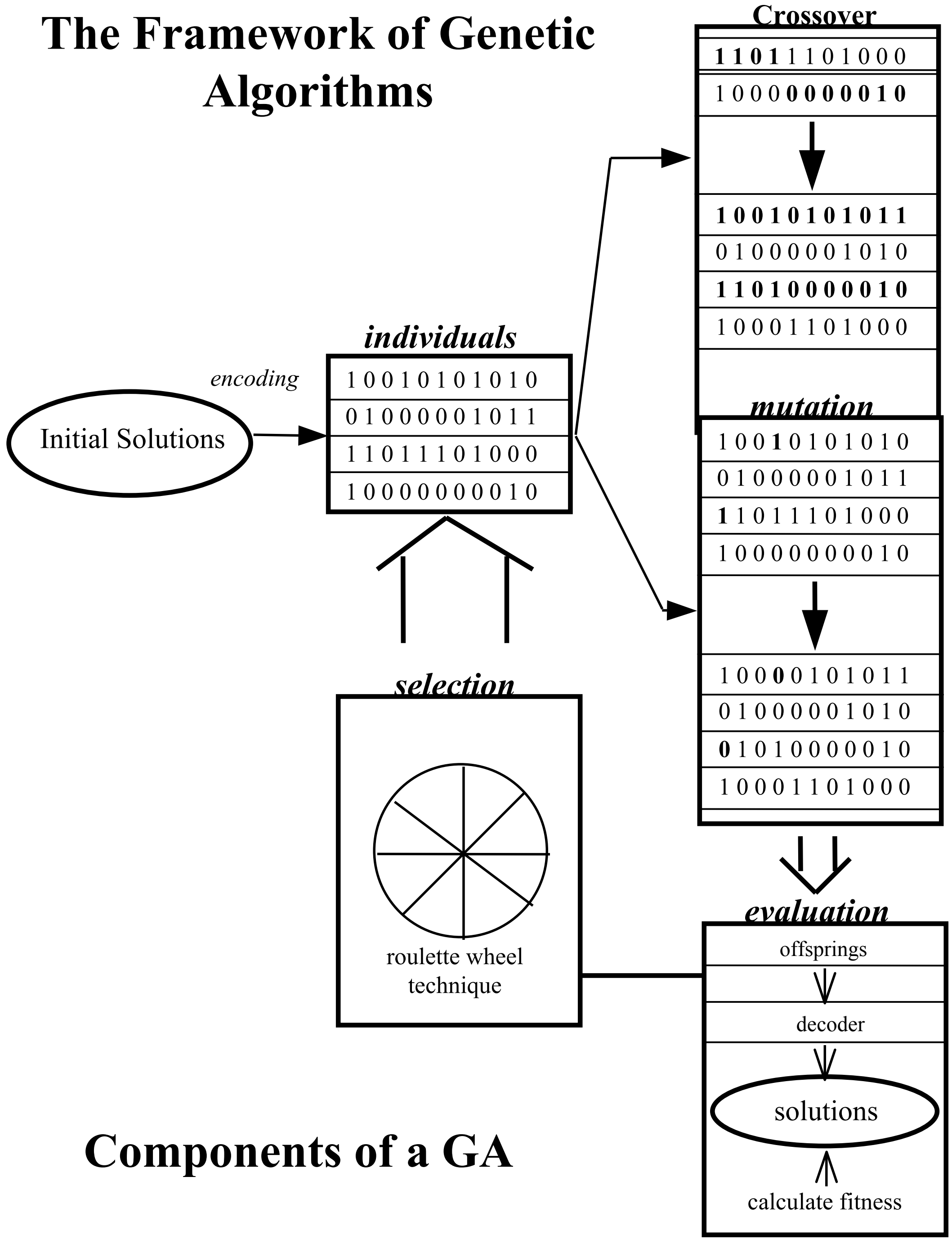
Associated Difficulties in Solving Inverse Problems In Electromagnetics

1. convergence difficulties, as with gradient or deterministic methods, when the object function has multiple local minimas or maximas.

2. convergence problems lead to inaccurate and unacceptable solutions.

3. random stochastic methods are, in general, inefficient or computationally intensive.

The Framework of Genetic Algorithms



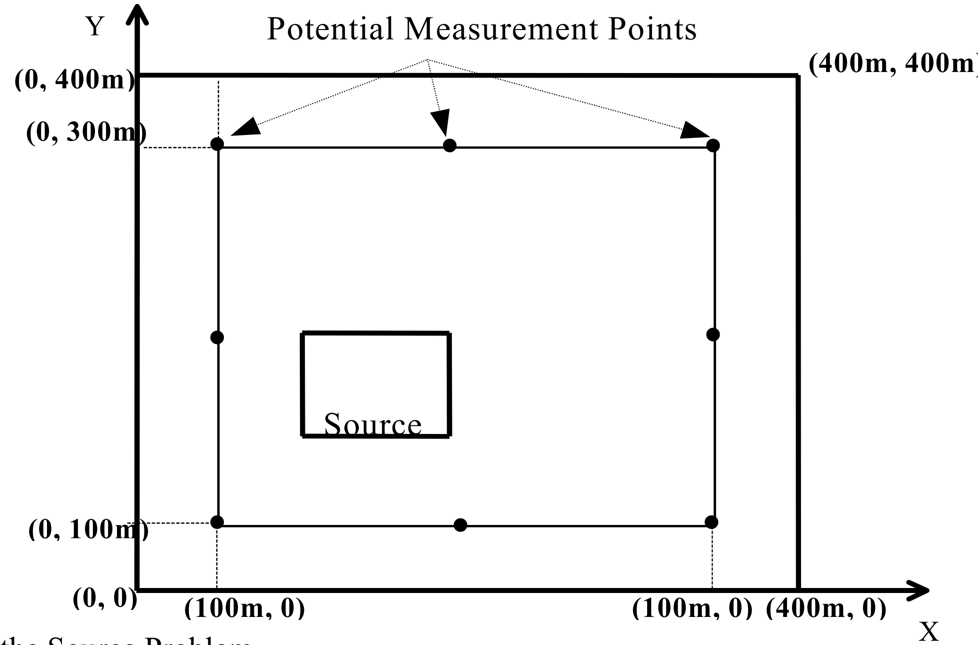
Components of a GA

THE SOURCE IDENTIFICATION PROBLEM

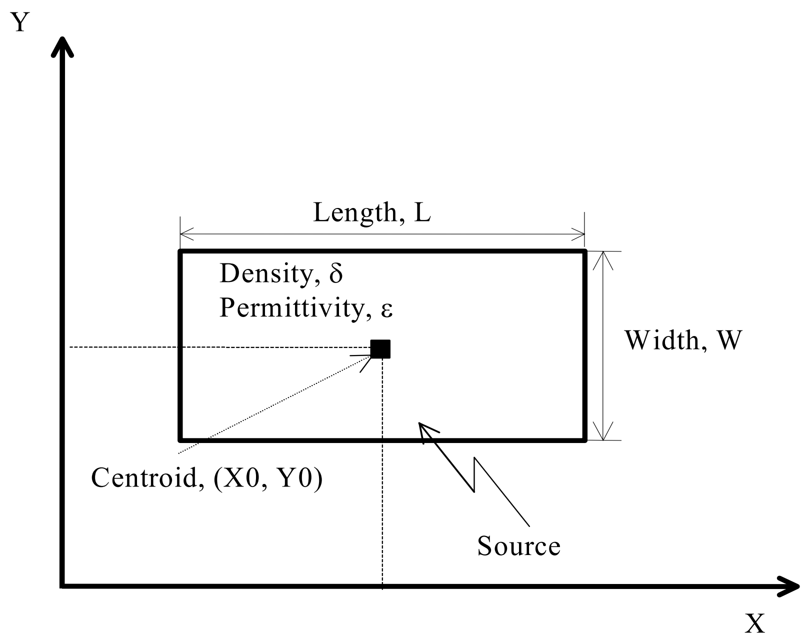
- An inaccessible region contains an electrostatic source or a charged region.
- The values of measured potentials, ϕ_m, for a test case are given.

Objective?

To correctly identify the various properties of the electrostatic source.



The Geometry of the Source Problem.



Object Function

n is the number of points at which the electrostatic potential is measured. In our case, n = 8.

$$F = \frac{1}{2}\sum_{i=1}^{n}(\phi_c^i - \phi_m^i)^2$$

Constraints

$$X + L/2 \leq 300 \qquad (1)$$

$$X - L/2 \geq 100 \qquad (2)$$

$$Y + W/2 \leq 300 \qquad (3)$$

$$Y - W/2 \geq 100 \qquad (4)$$

$$a < \delta < b \qquad (5)$$

$$c < \varepsilon < d \qquad (6)$$

The Parameters of GA Optimization

Number of Iterations	**50**
Number of Field Evaluations	**500**
Population	**10**
String Length	**120**
Probability of Mutation	**0.39 to 0.03**
Probability of Crossover	**0.95**

THE CRACK IDENTIFICATION PROBLEM

Objective: To identify the irregularities or defects in inaccessible locations using nondestructive testing (NDT). Specifically, it is required to identify the exact nature of a crack present in a conducting medium.

Problem Challenges:

1. A rough object function with several minimas.
2. A gradient algorithm used previously could not converge satisfactorily. Several techniques had to be applied before satisfactory results were achieved.

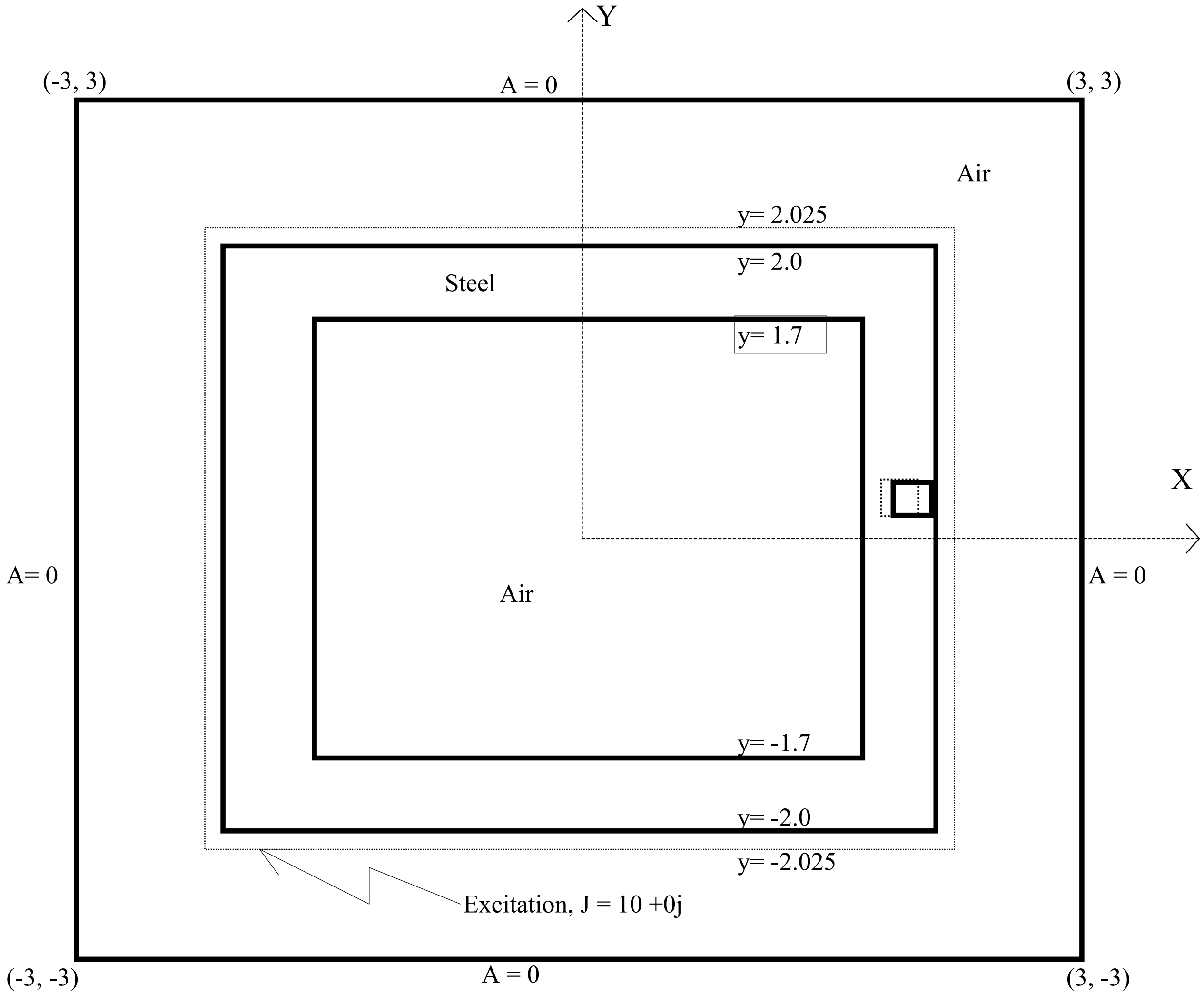
Features of FEM combined with Optimization (GAs) for Nondestructive Testing

- Conventional methods of NDE, like moving a coil over a magnetic system, only inform us about the existence of a defect.

- No information is generated about its nature.

PARAMETER IDENTIFICATION PROBLEM

L = the length of the crack,
W = the width of the crack,
ϑ = *the orientation of the crack,*
$X0$ = *the X-coordinate of the centroid of the crack*
$Y0$ = *the Y-coordinate of the centroid of the crack.*



Y
(-3, 3)
A = 0
(3, 3)
Air
y= 2.025
y= 2.0
Steel
y= 1.7
X
A= 0
A = 0
Air
y= -1.7
y= -2.0
y= -2.025
Excitation, J = 10 +0j
(-3, -3)
A = 0
(3, -3)

Performance Prediction of SRM Drive Systems Under Normal and Fault Operating Conditions Using GA-Based ANN Method

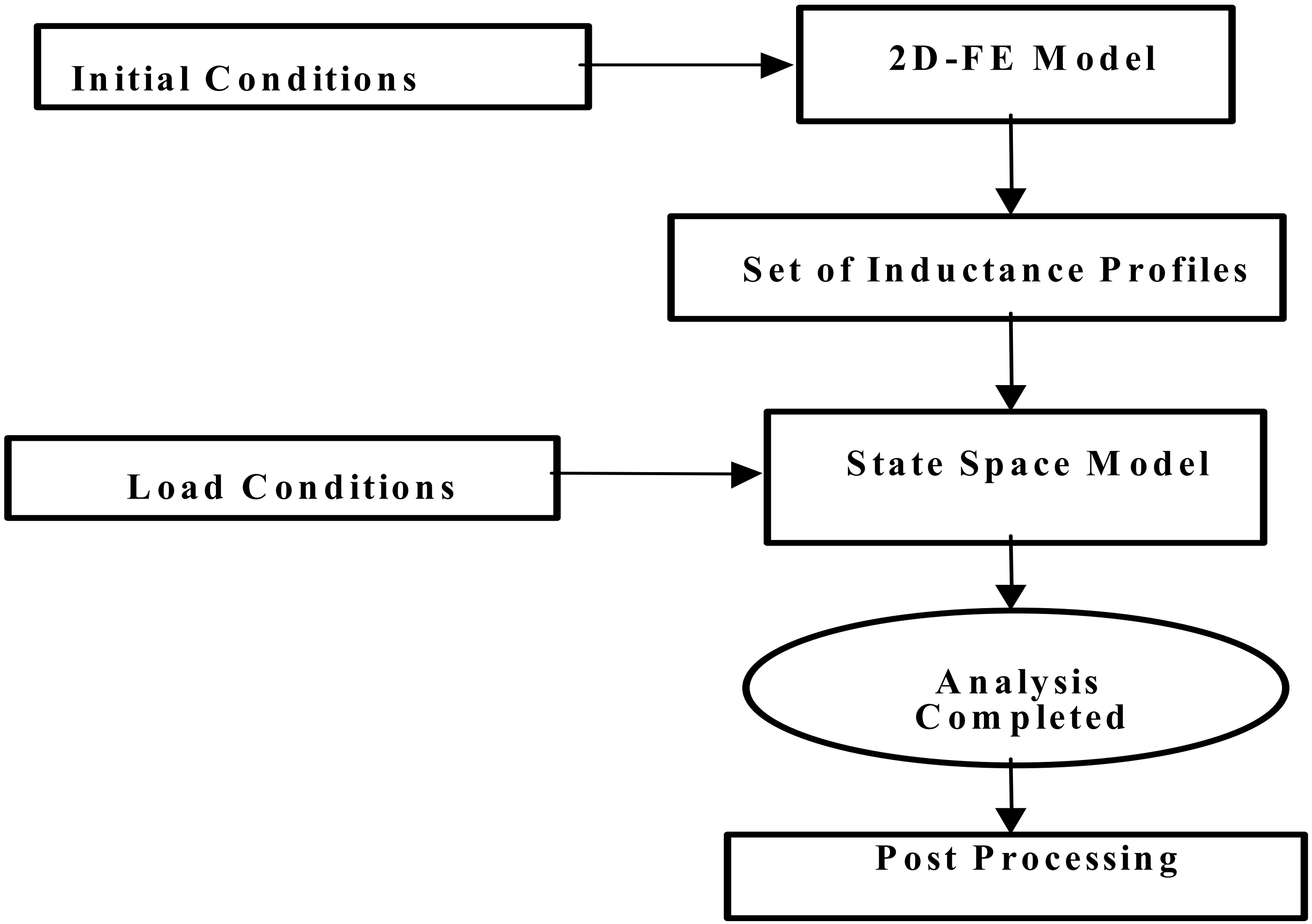
THE MODELING ENVIRONMENT

The modeling environment consists of three main components:

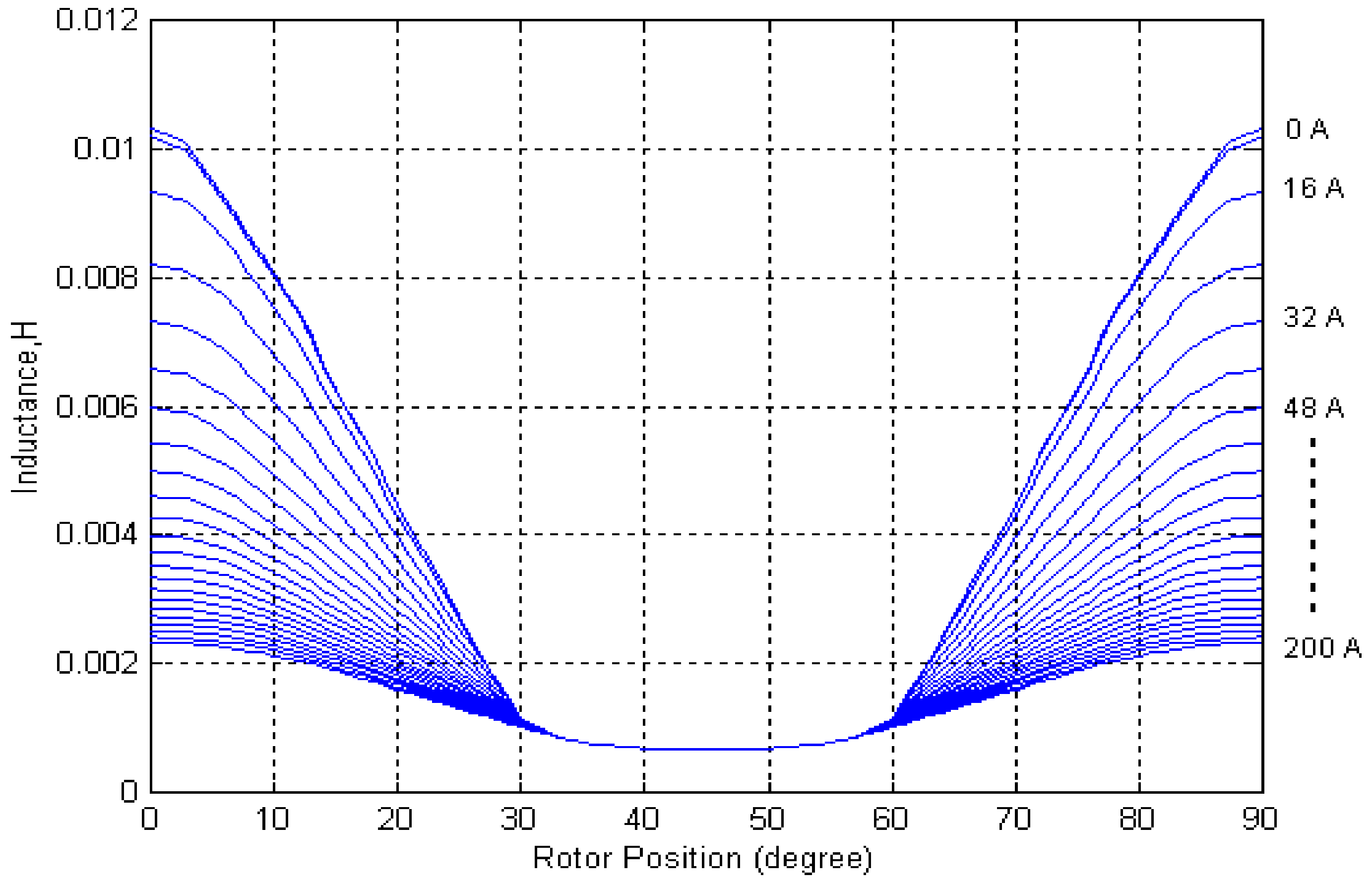
- The first is an electromagnetic/electric circuit algorithm that indirectly couples FE/SS models.

- The second component uses ANNs, for their well known interpolation capabilities for highly nonlinear systems, to predict the performance characteristics of an SRM drive system.

- The third uses GAs for their ability to search a complex structural and parametric space to find good ANN solutions.



Flowchart of Multi-curve FE/SS Approach



SRM Inductance Family of Curves

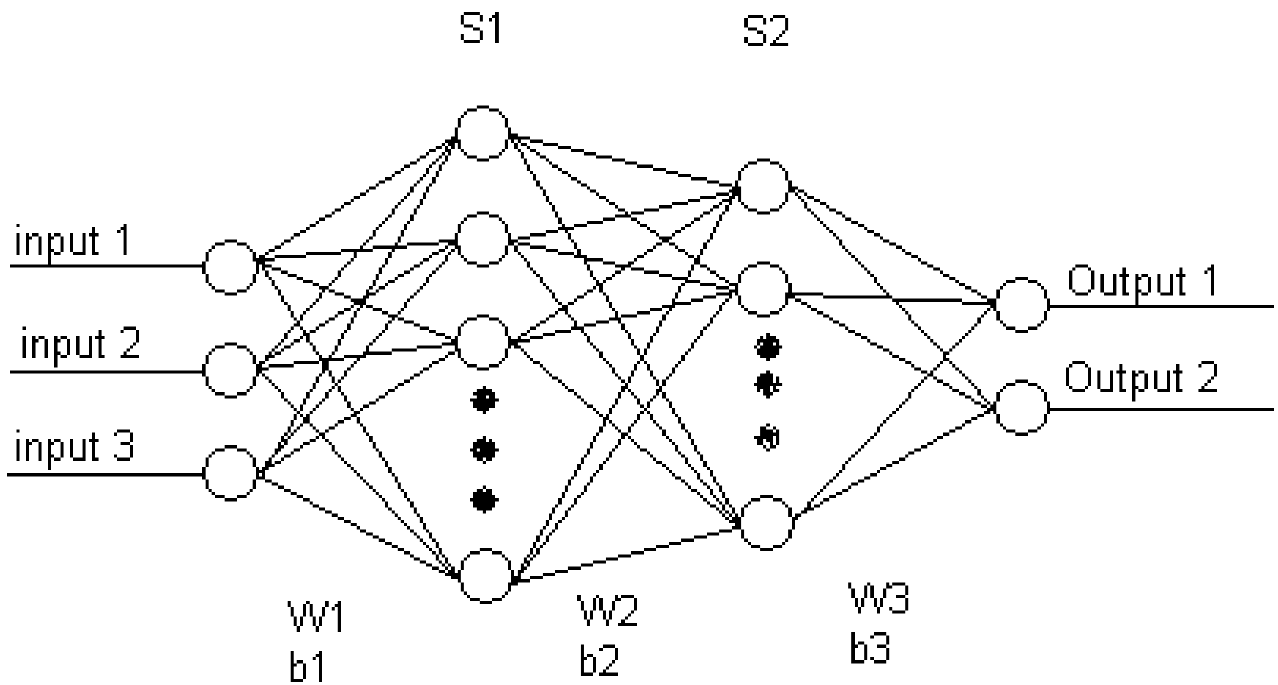
A New Method of Searching for an Optimal Neural Network Using Genetic Algorithms

- In this work, a new encoding method is introduced. Rather than binary or real number encoding as introduced before, matrices are taken as elements in a string.

- Compared to the traditional way of encoding the weights as a list, the primary advantage of matrix encoding is that the population consists of individuals that represent various ANN structures.

- Therefore, using GA operators can not only search for optimal weights and biases but also a wide range of possible structures are explored.

- As a result of using matrices as elements of a string the definitions of the genetic operators, mutation and crossover, are expanded so as they can be applied to matrices.



Structure of a feedforward ANN

$$
\overset{A}{\begin{bmatrix} a11 & a12 & a13 & a14 \\ a21 & a22 & a23 & a24 \\ a31 & a32 & a33 & a34 \\ a41 & a42 & a43 & a44 \\ a51 & a52 & a53 & a54 \end{bmatrix}}
\quad
\begin{bmatrix} a23 & a24 \\ a33 & a34 \\ a43 & a44 \end{bmatrix} + \begin{bmatrix} r11 & r12 \\ r21 & r22 \\ r31 & r32 \end{bmatrix} \Longrightarrow
\quad
\overset{A'}{\begin{bmatrix} a11 & a12 & a13 & a14 \\ a21 & a22 & a23' & a24' \\ a31 & a32 & a33' & a34' \\ a41 & a42 & a43' & a44' \\ a51 & a52 & a53 & a54 \end{bmatrix}}
$$

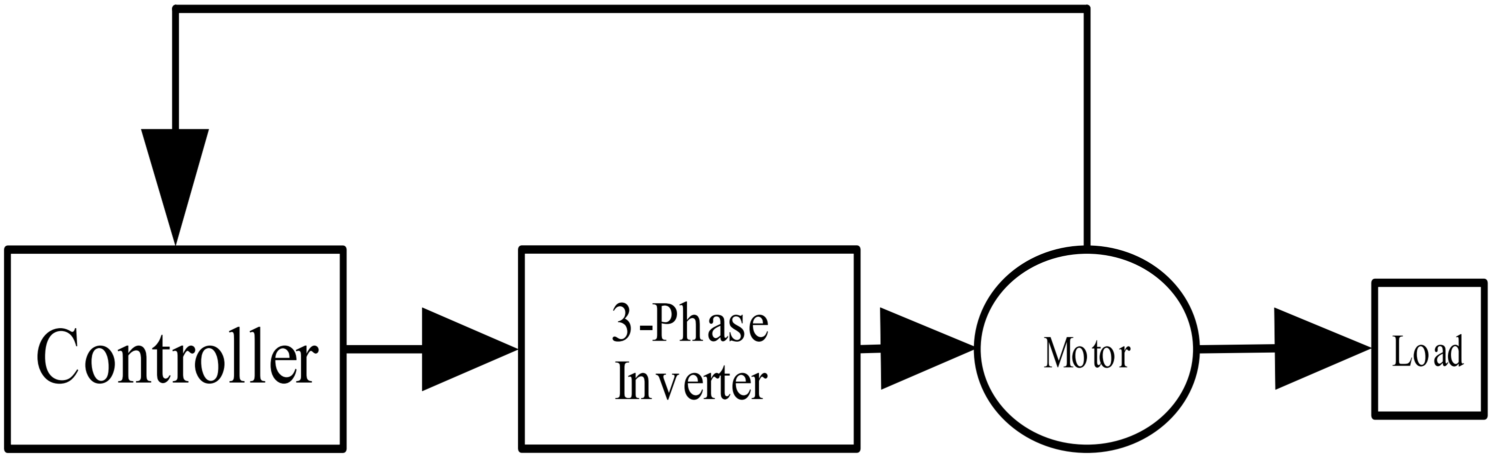
Definition of Matrix Mutation

$$A = \begin{bmatrix} a11 & a12 & a13 & a14 \\ a21 & a22 & a23 & a24 \\ a31 & a32 & a33 & a34 \\ a41 & a42 & a43 & a44 \\ a51 & a52 & a53 & a54 \end{bmatrix} \qquad B = \begin{bmatrix} b11 & b12 & b13 \\ b21 & b22 & b23 \\ b31 & b32 & b33 \end{bmatrix}$$

$$\Downarrow$$

$$A' = \begin{bmatrix} a11 & a12 & a13 & a14 \\ a21 & a22 & b21 & b22 \\ a31 & a32 & b31 & b32 \\ a41 & a42 & a43 & a44 \\ a51 & a52 & a53 & a54 \end{bmatrix} \qquad B' = \begin{bmatrix} b11 & b12 & b13 \\ a23 & a24 & b23 \\ a33 & a34 & b33 \end{bmatrix}$$

Definition of Matrix Crossover



SRM Drive System

A CASE STUDY

- The modeling environment presented in this paper is used to characterize an SRM drive system under three different operating conditions:
  - normal (no-fault)
  - loss of a phase (fault)

    occurs when a transistor burns out or a fuse in the phase leg opens out, creating an open circuit in one phase of the motor and resulting in the loss of one phase
  - partial phase short (fault).

    takes place when part of the turns forming a stator winding is shorted. In such case, all the phases are still in operation except that the faulted phase has less effective number of turns.

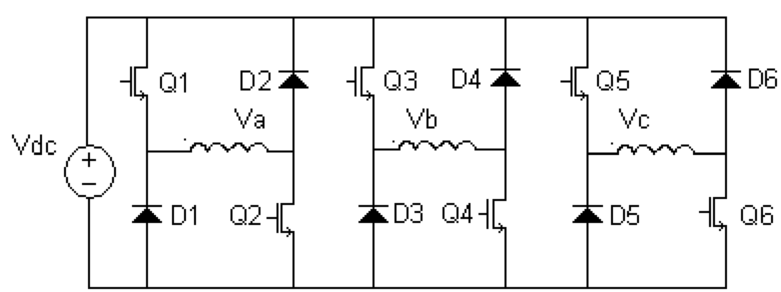
- Also based on the topology of the machine and the power electronic inverter used, a state space model was developed for the SRM.

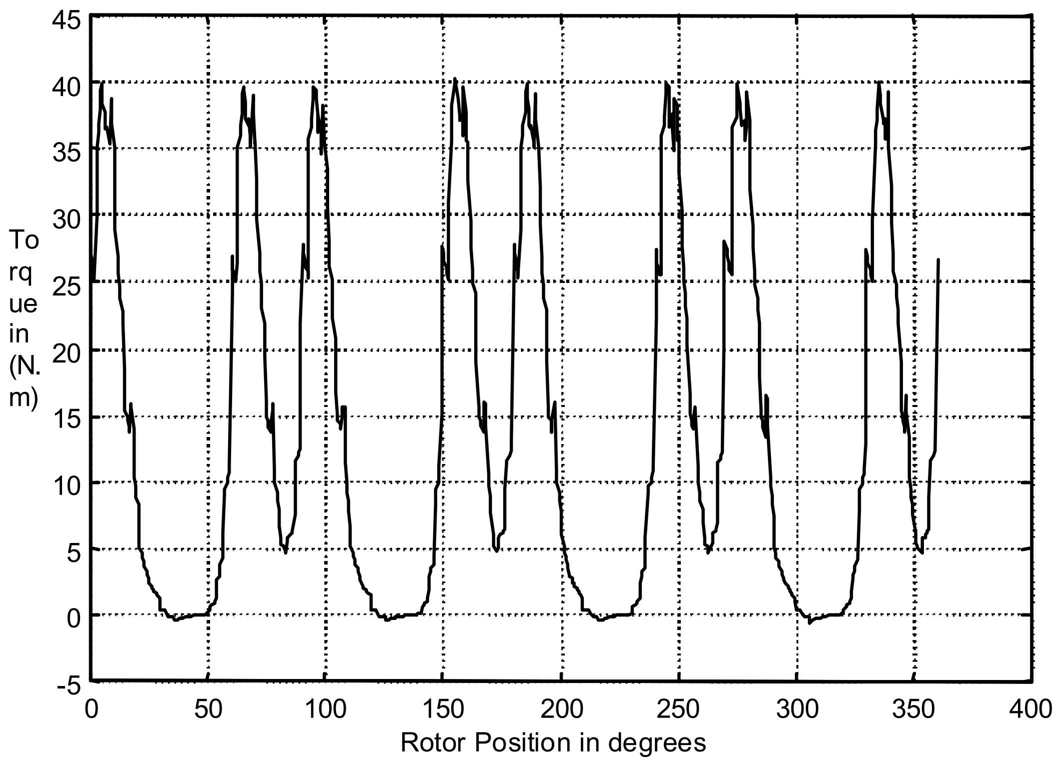
- The state space equations can be written as follows:

$$V_k = RI + L\,dI/dt + \omega_m I\,dL/d\theta \qquad (1)$$

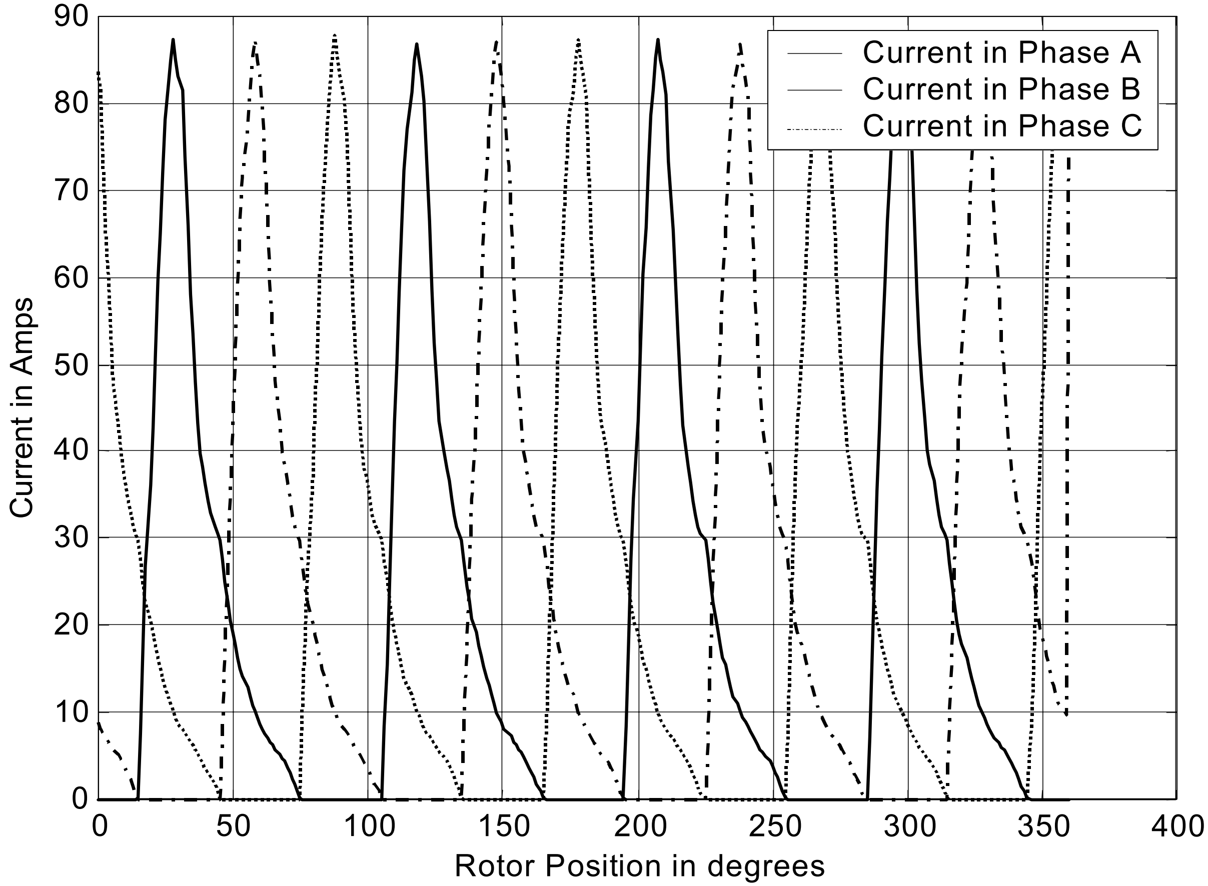
$$d\omega_m/dt = (T_{em} - B\omega - T_L)/J \qquad (2)$$

$$T_{em} = \Sigma\ i_k^2 dL_k \qquad k = a,\ b,\ c \qquad (3)$$





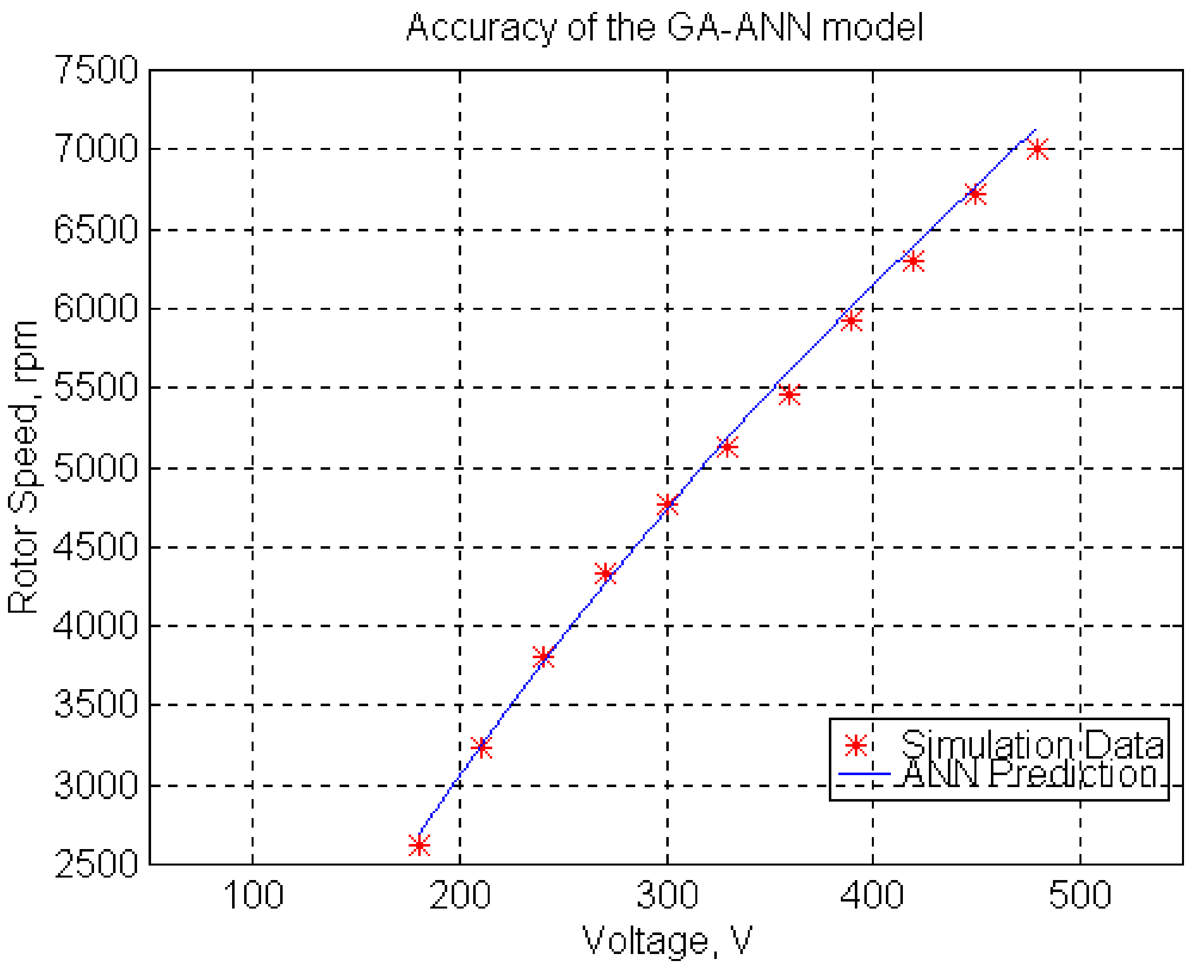
Developed Torque profile due to a Loss of Phase Fault Condition



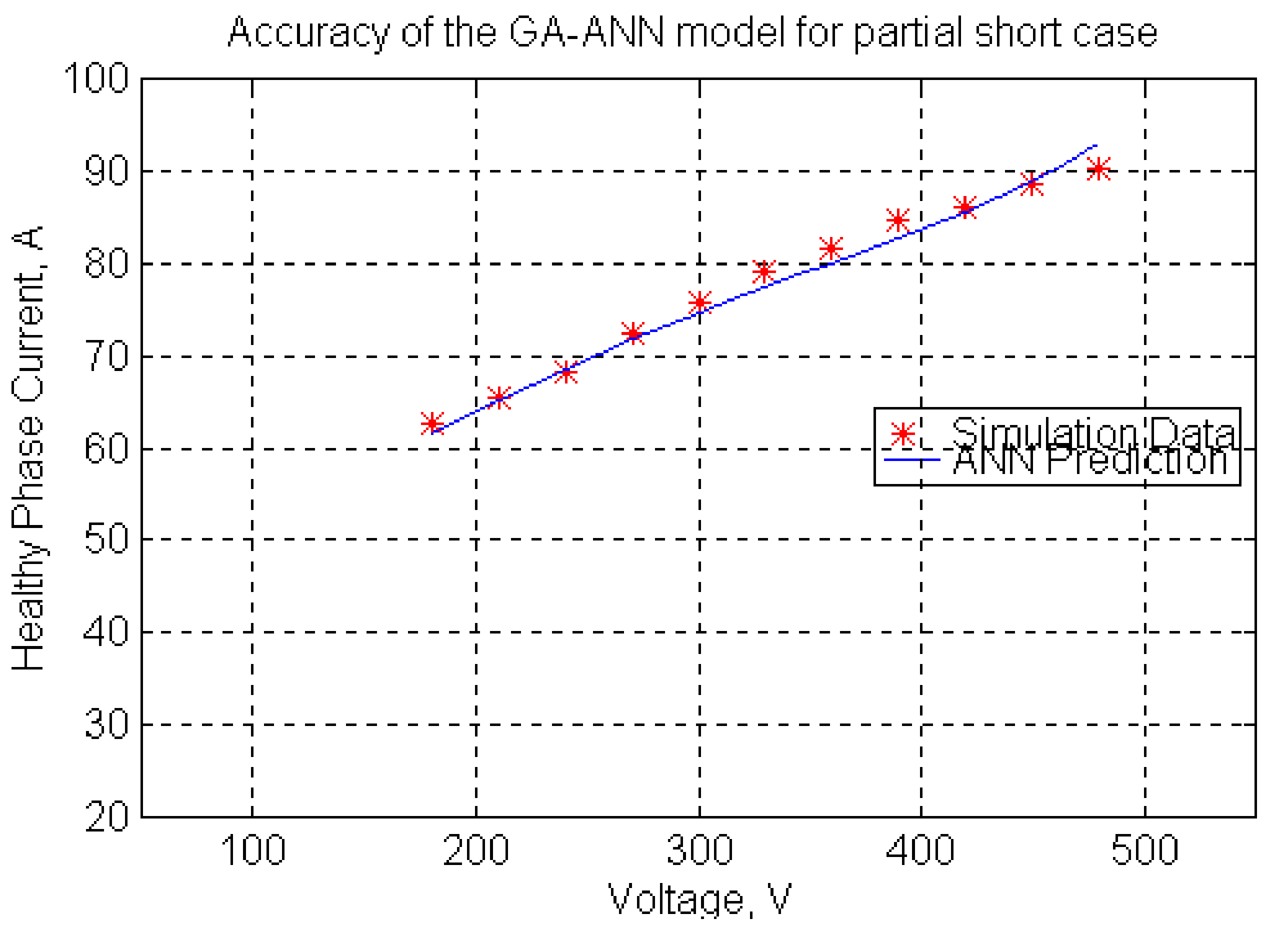
Current in the three Phases a, b, c for No Fault Case

Type of Data	Shaft Speed (rpm)	RMS current (Amps)
Simulation	8985	34.02
Experimental	9013	34.85

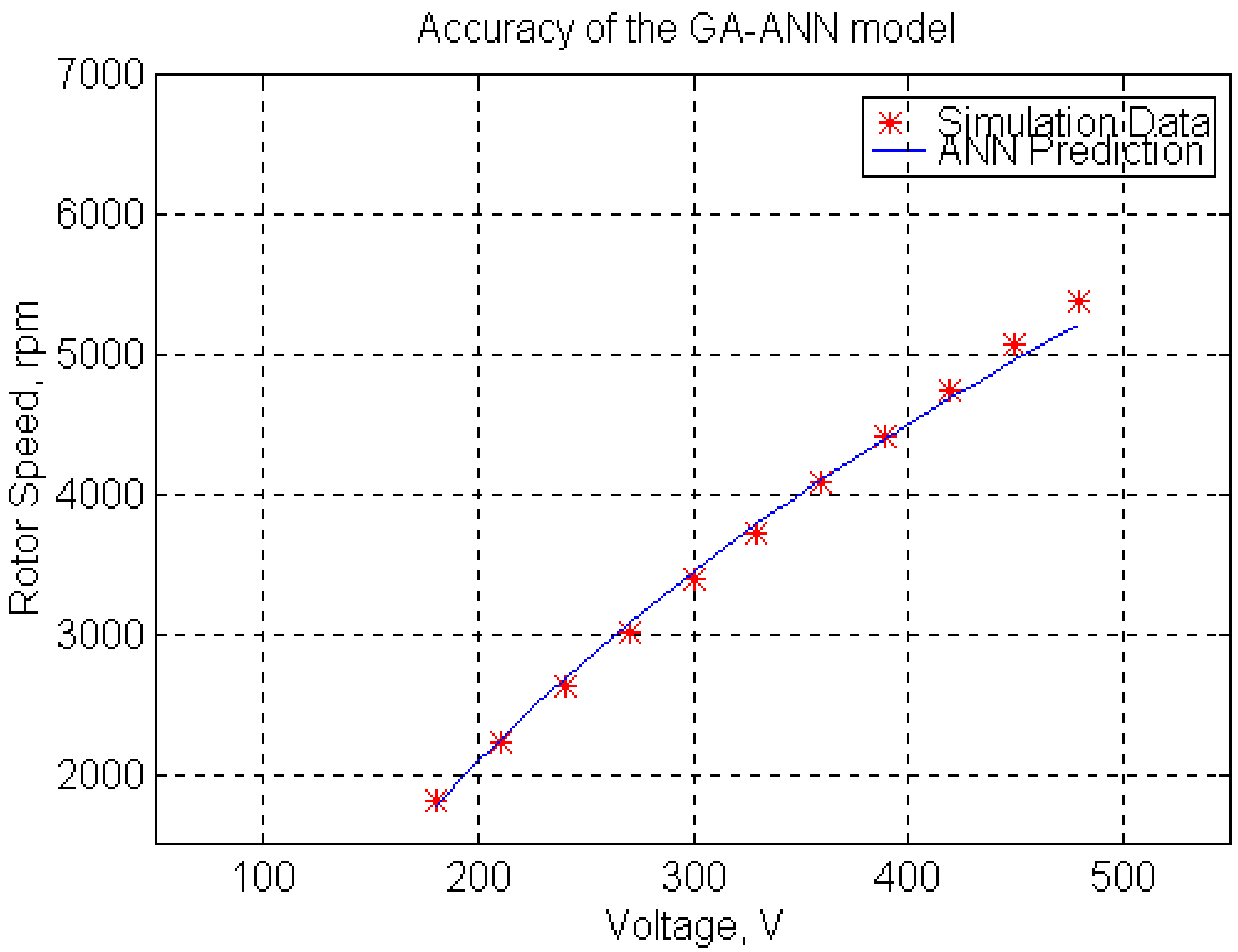
Table: Comparison of Simulation and Experimental Results



ANN model Speed Results for Normal (no-fault) Case

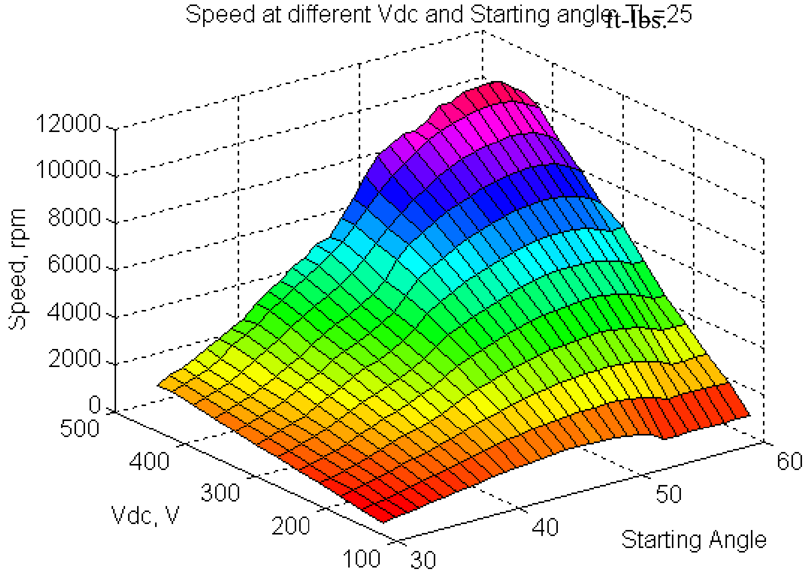


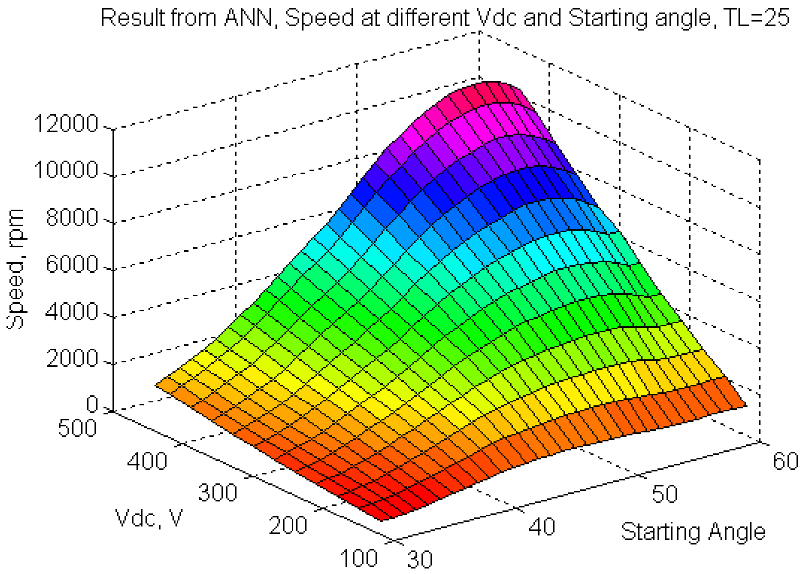
ANN Model of Healthy Phase Current Results
for Partial Fault Case



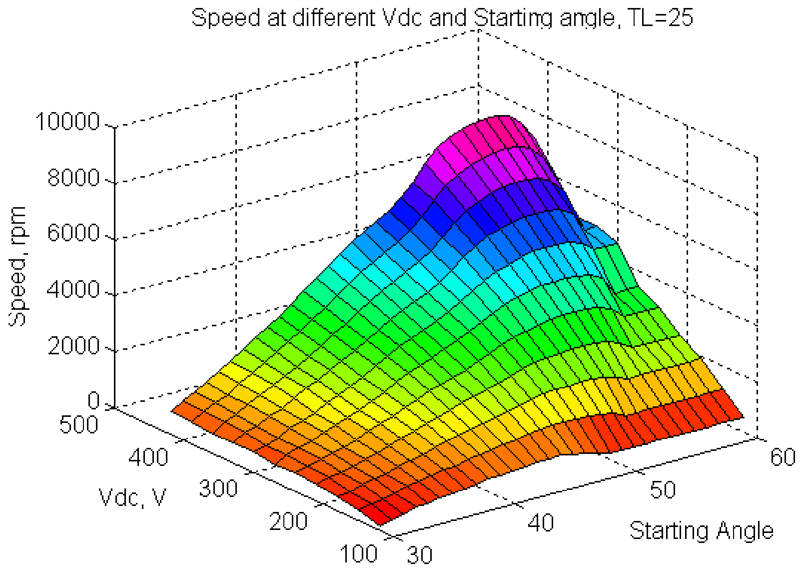
Rotor Speed Prediction of ANNs at One Phase Failure Case

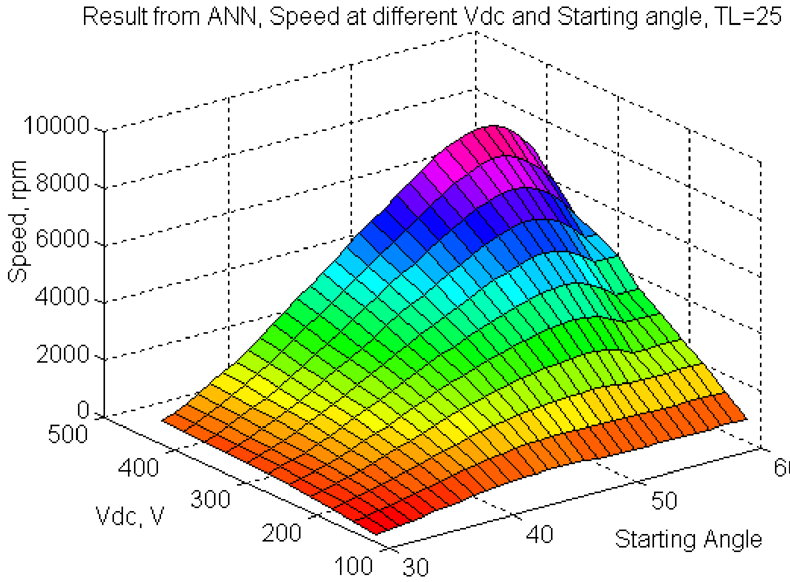
Comparison of FE/SS data and results from ANN model at TL=25 ft-lbs. (Normal Case)



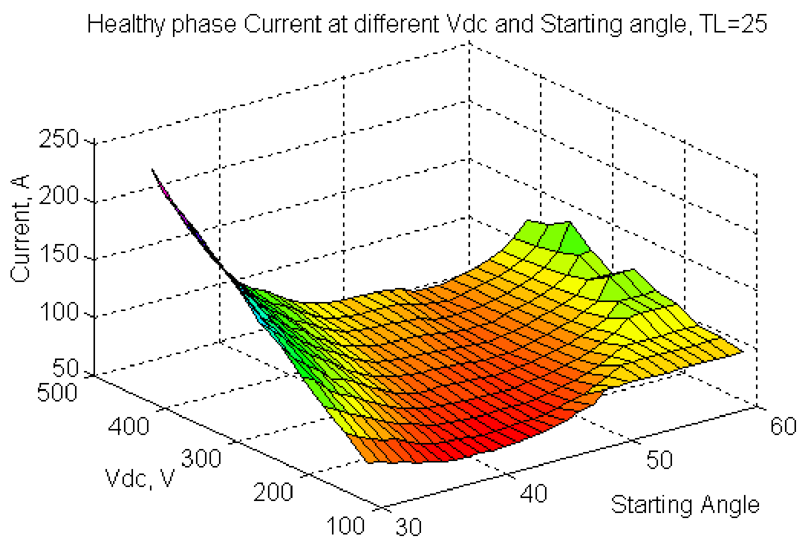


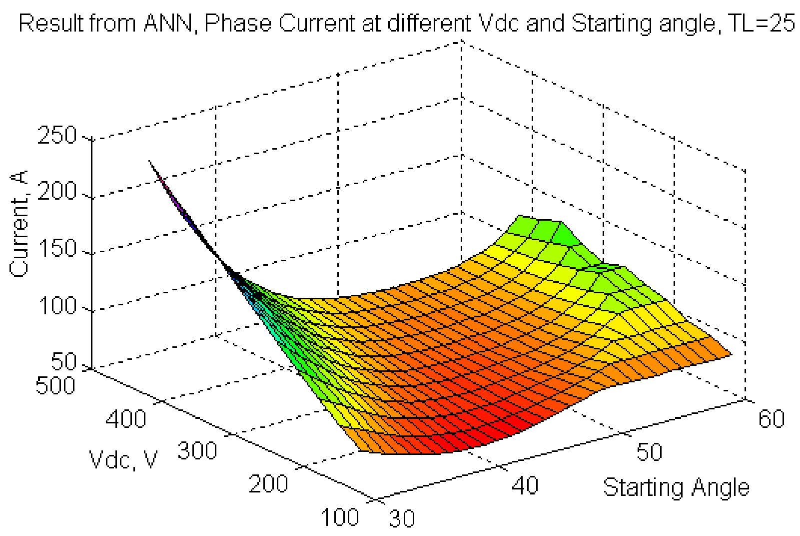
Comparison of FE/SS data and results from ANN model at a phase failure case, Tl=25 ft-lbs. (Loss of a Phase)



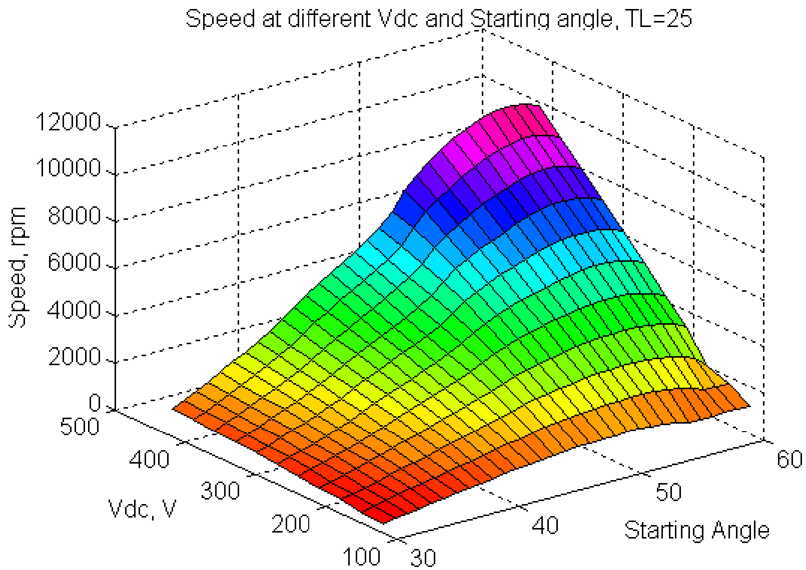


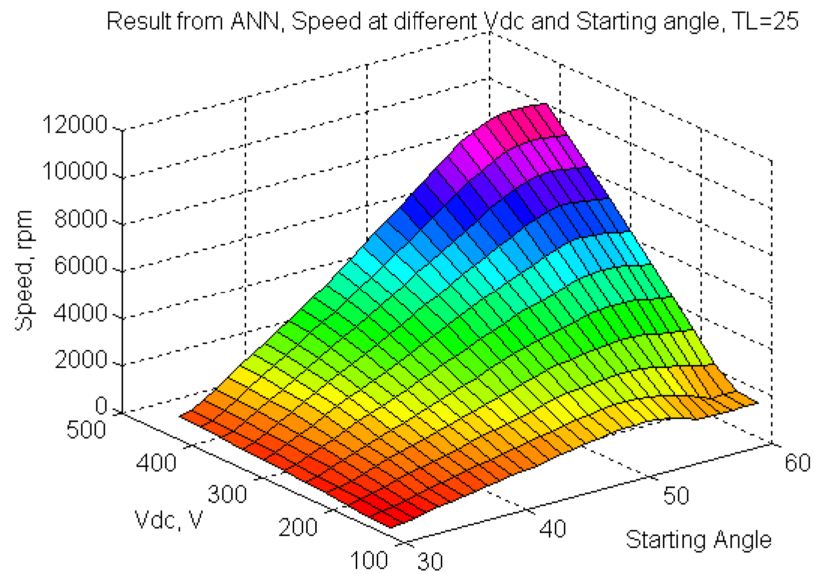
Comparison of FE/SS and results from ANN model at a phase failure case, Tl=25 ft-lbs. (Loss of a Phase)



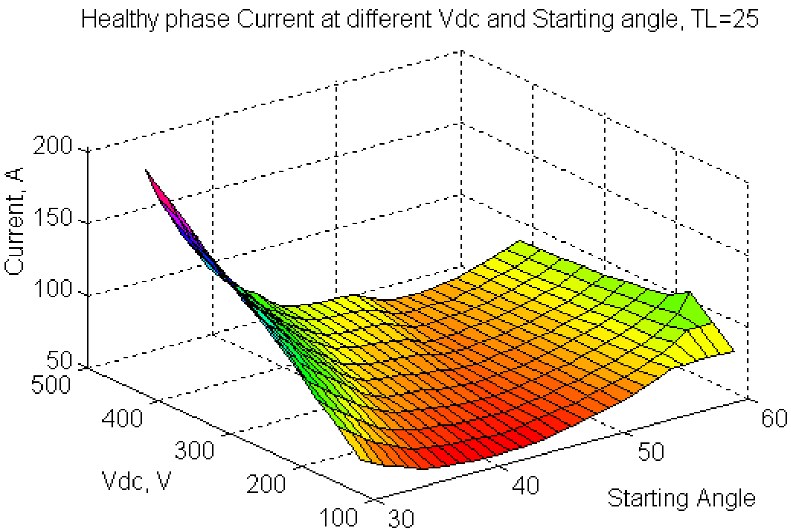


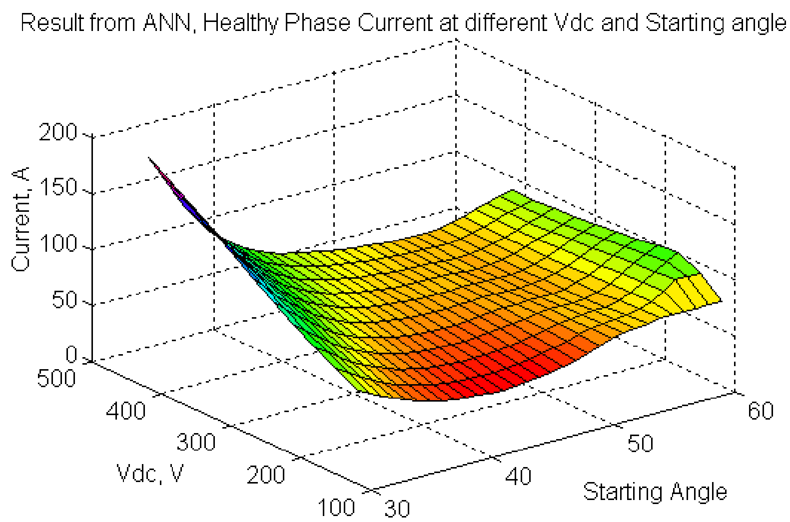
Comparison of FE/SS and results from ANN model at a phase short case, Tl=25 ft-lbs. (50% Phase Short)





Comparison of FE/SS and results from ANN model at a phase short case, Tl=25 ft-lbs.
(50% Phase Short)





Characterization of SRM Drives Using Fuzzy Inference Systems

Abstract

- A fuzzy inference system is used to characterize switched reluctance motor, SRM, drive systems under normal and fault operating conditions.

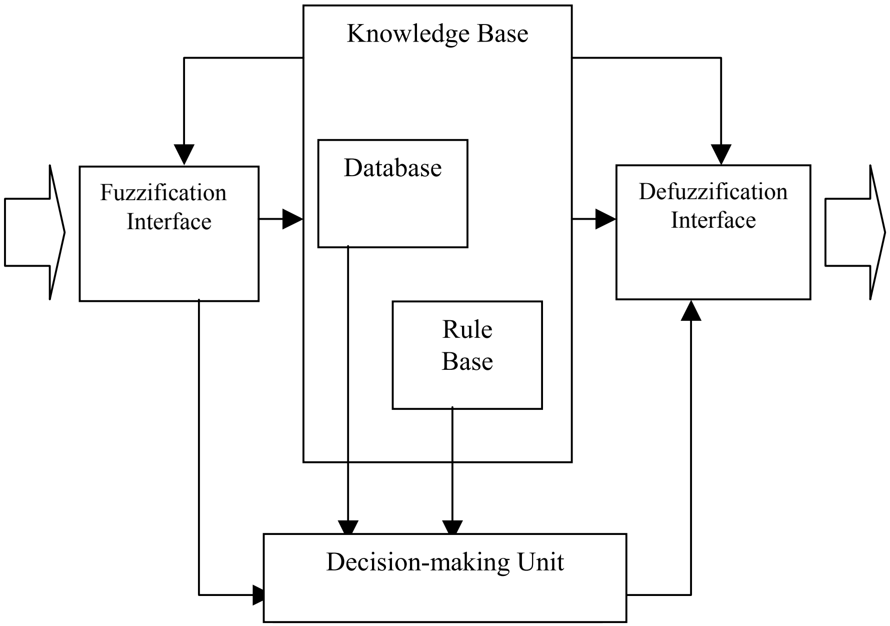
- The Fuzzy Logic (FL) is applied for its ability to be very suitable for problems with large uncertainly.

- Knowledge about the system is accumulated using coupled Finite-Element (FE) magnetic field and state space (SS) models.

Fuzzy Inference System (FIS)

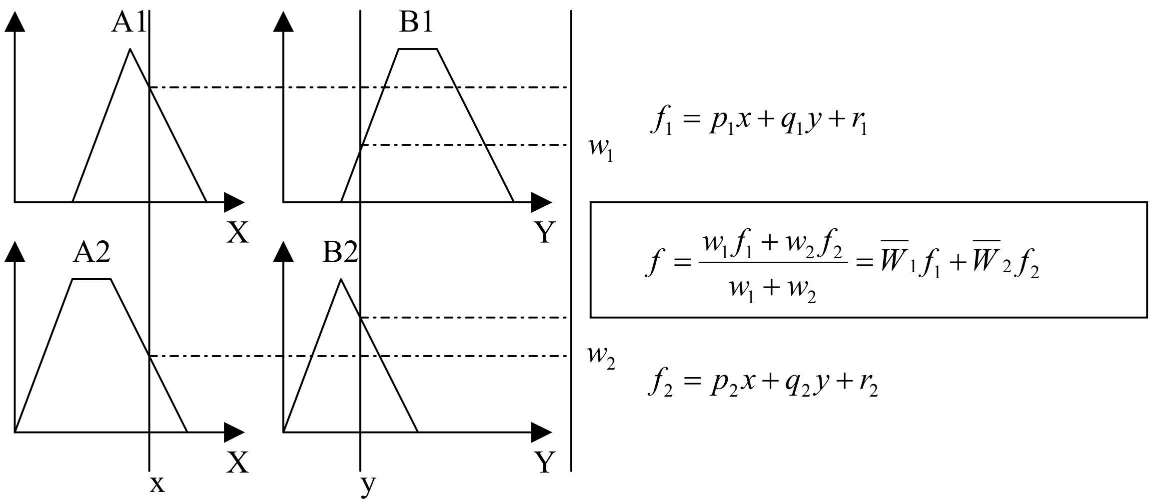
*The FL modeling approach is based on the use of Fuzzy Inference Systems.

- **The FIS consists of:**
  - ***rule base* containing a number of IF-THEN rules,**
  - ***database* that defines the membership functions,**
  - ***decision-making unit* that performs the inference operations,**
  - ***fuzzification interface* that transforms the crisp inputs into degree of match, and**
  - ***defuzzification interface* that transforms the fuzzy results to crisp output.**

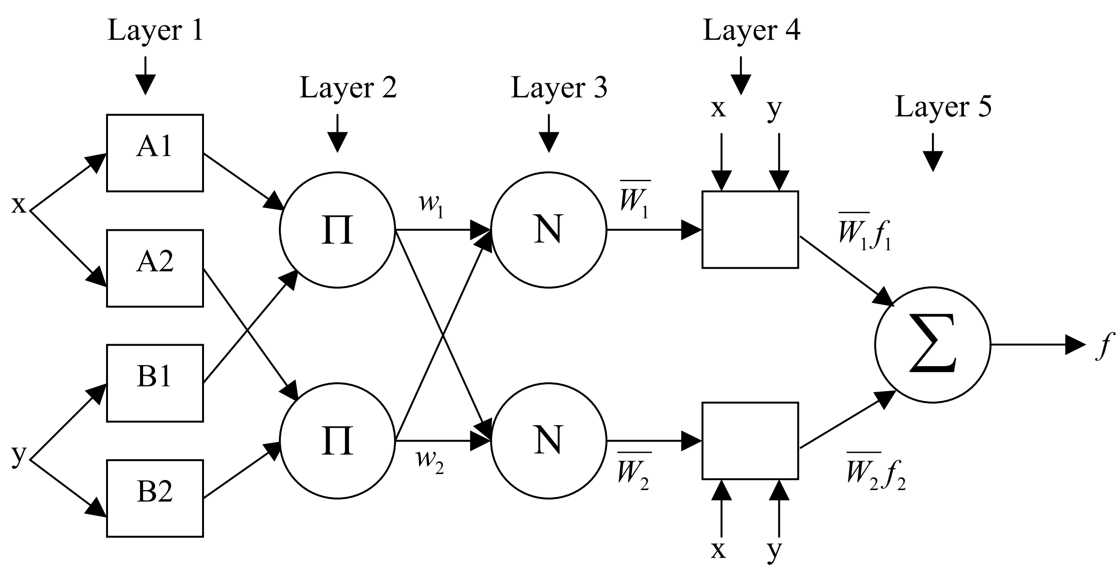


Fuzzy Inference System

Adaptive-Network-Based FIS (ANFIS)

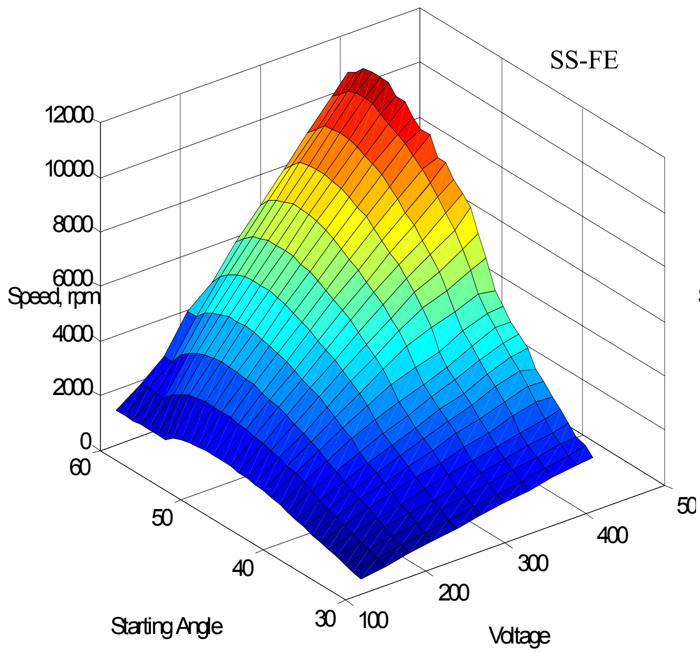


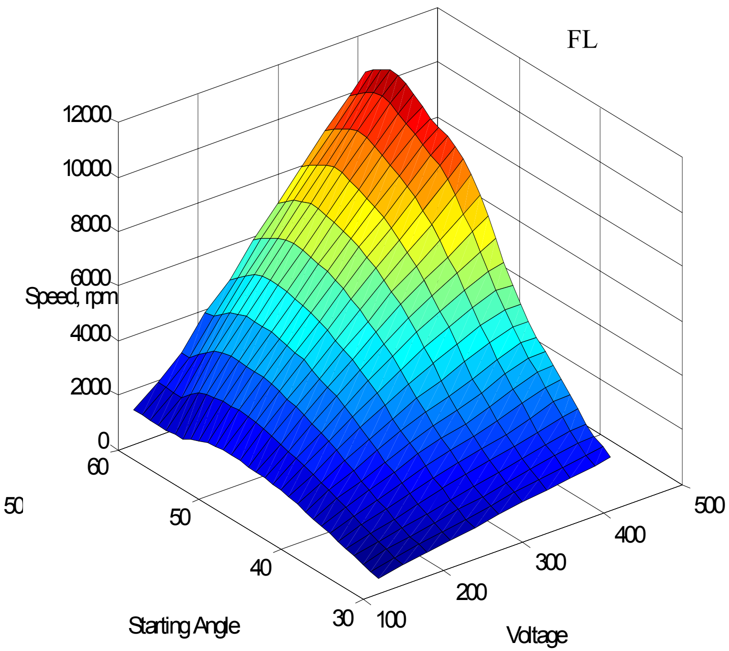
Type-three Fuzzy Reasoning



Equivalent ANFIS

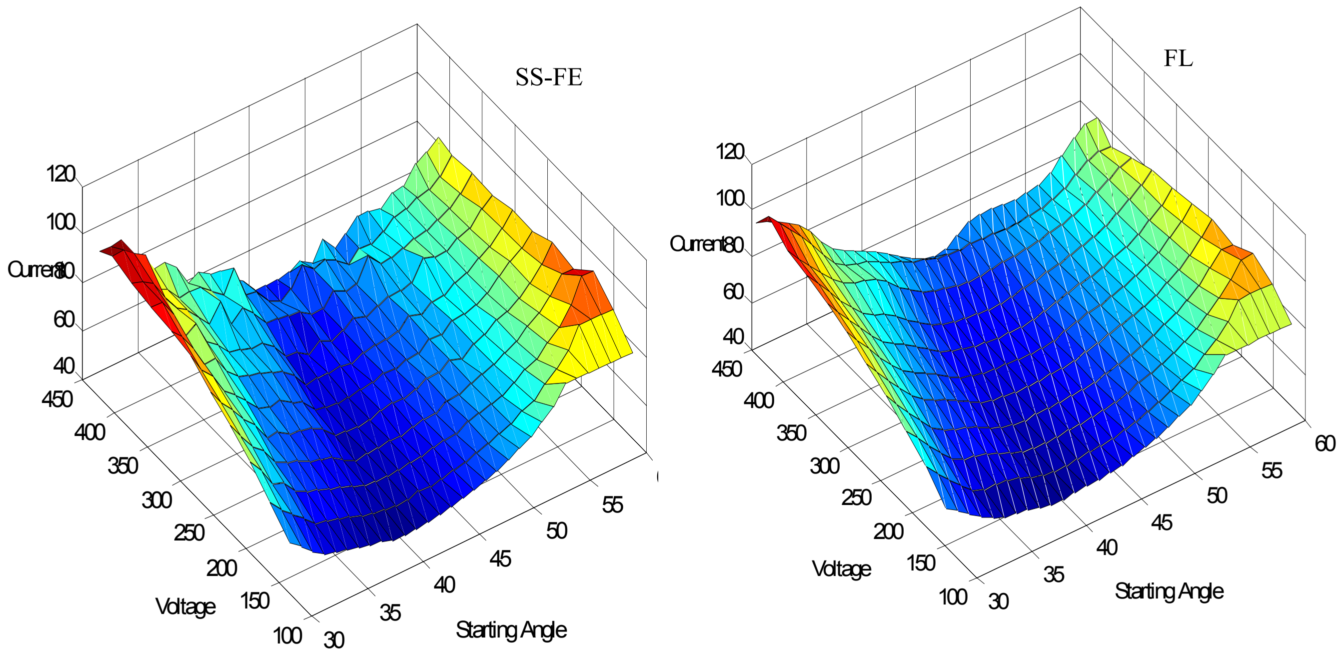
Result Analysis





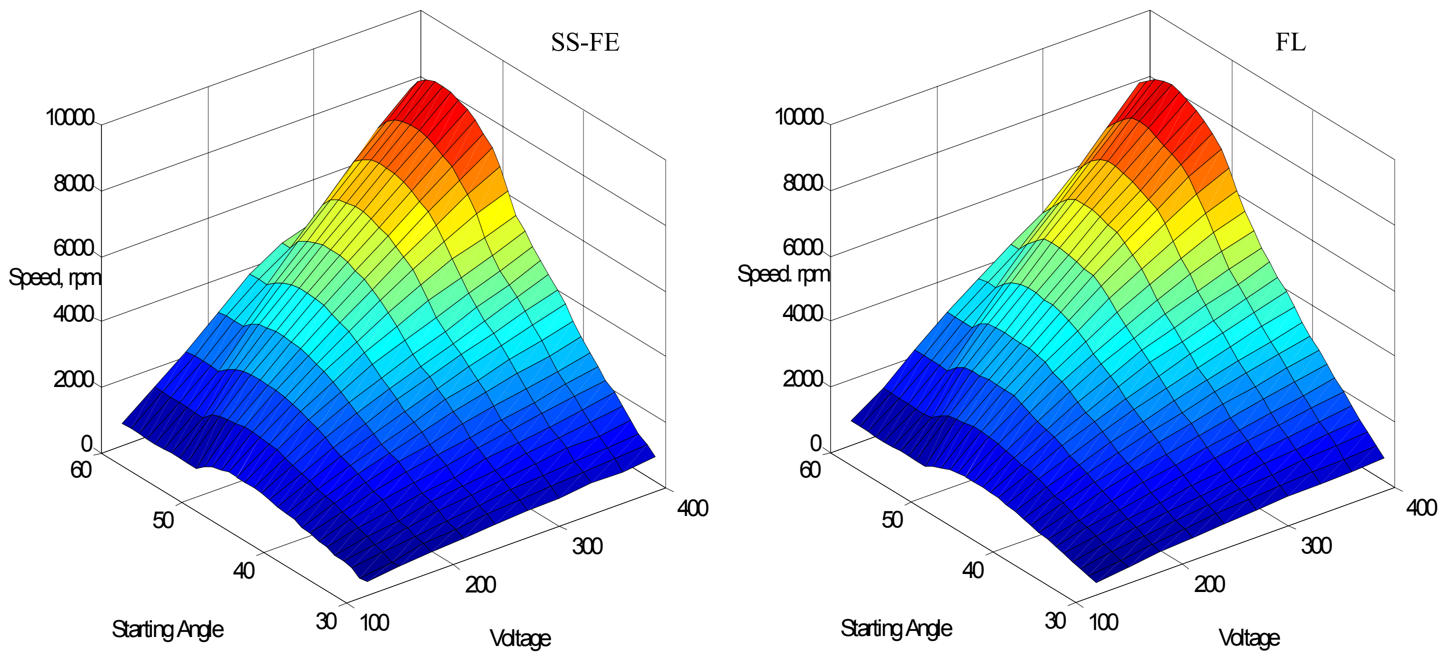
Speed Generated from the SS-FE Model and the FL Model (Normal Case) at Different DC Voltage and Starting Angel (Fixed Torque Load TL = 20 ft-lb)

Result Analysis (continued)



Current Generated from the FE-SS Model and the FL Model (Normal Case) at Different DC Voltage and Starting Angel (Fixed Torque Load TL = 20 ft-lb)

Result Analysis (continued)



Speed Generated from the FE-SS Model and the FL Model (Under Phase Loss) at Different DC Voltage and Starting Angel (Fixed Torque Load TL = 20 ft-lb)

Result Analysis (continued)

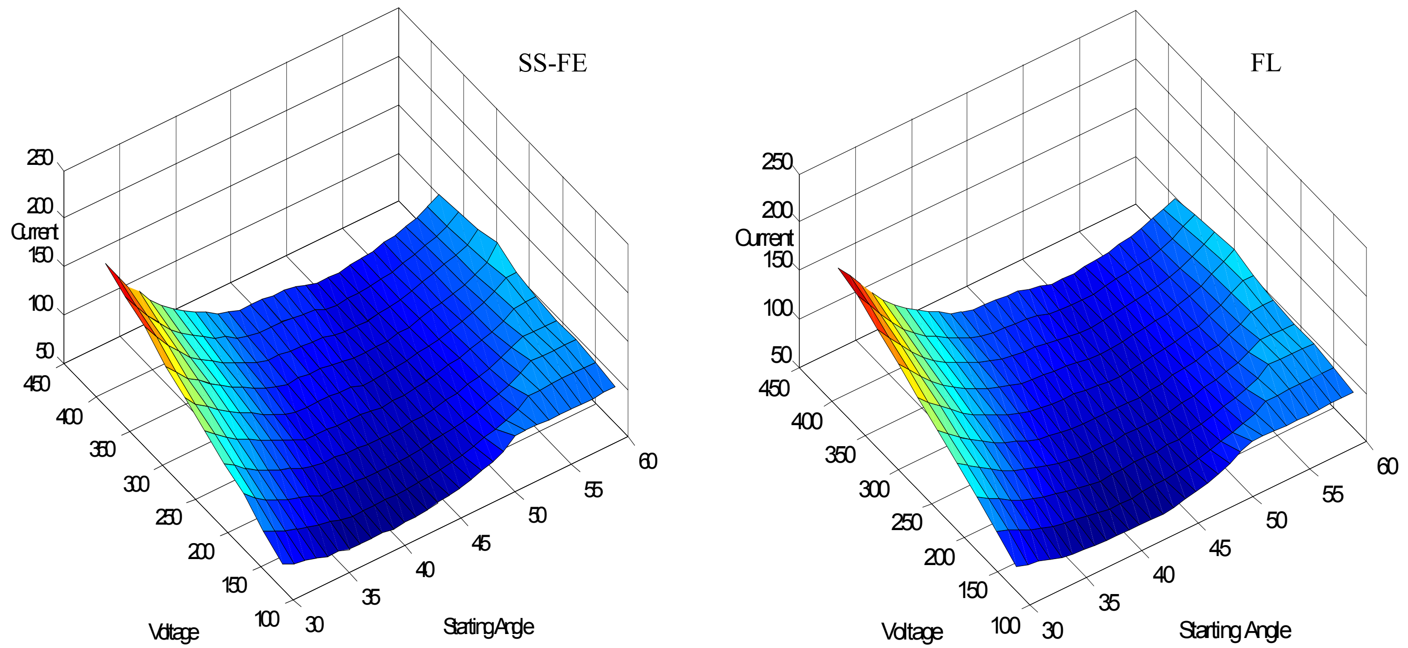
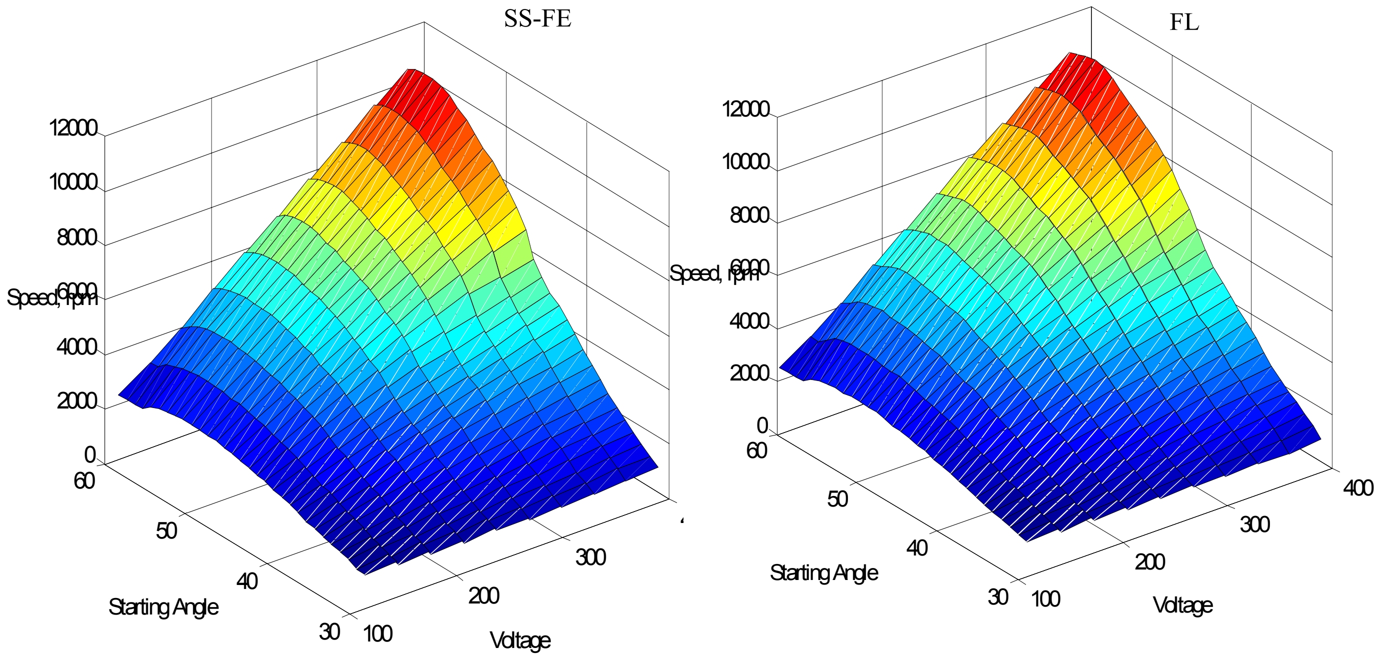


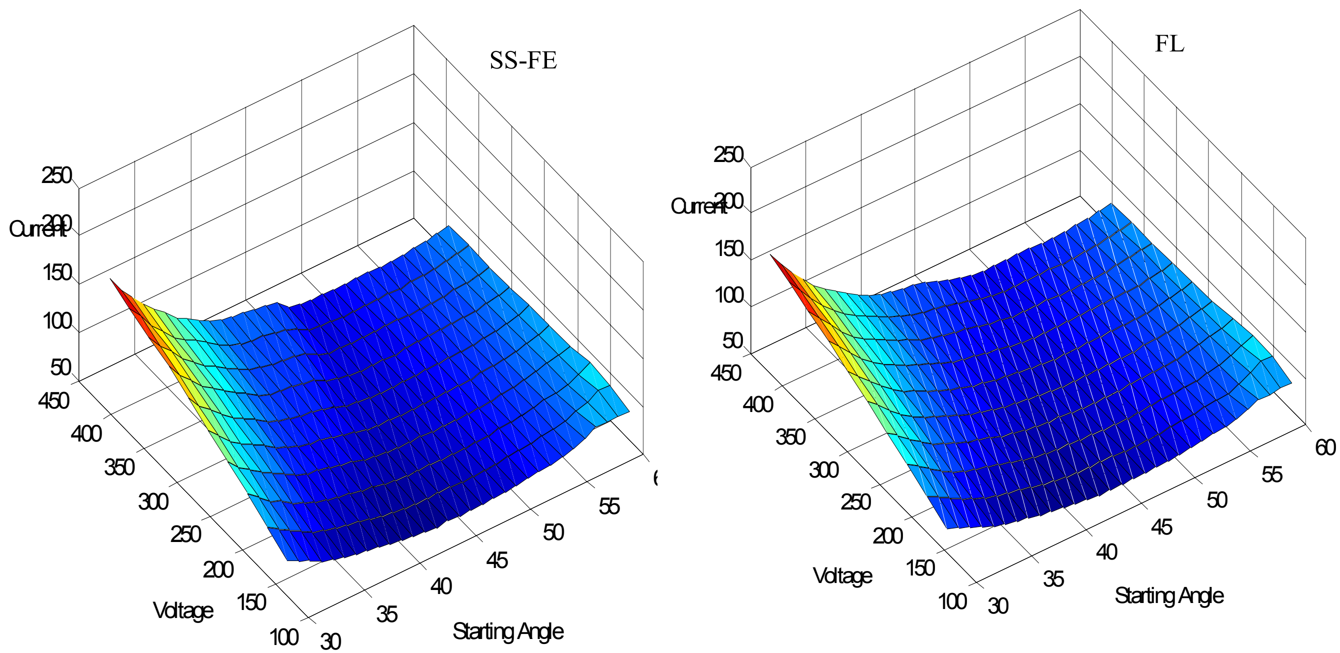
Figure 8-10-a: Current Generated from the SS-FE Model (Under Phase Loss) at Different DC Voltage and Starting Angel (Fixed Torque Load TL=20 ft-lb)

Result Analysis (continued)



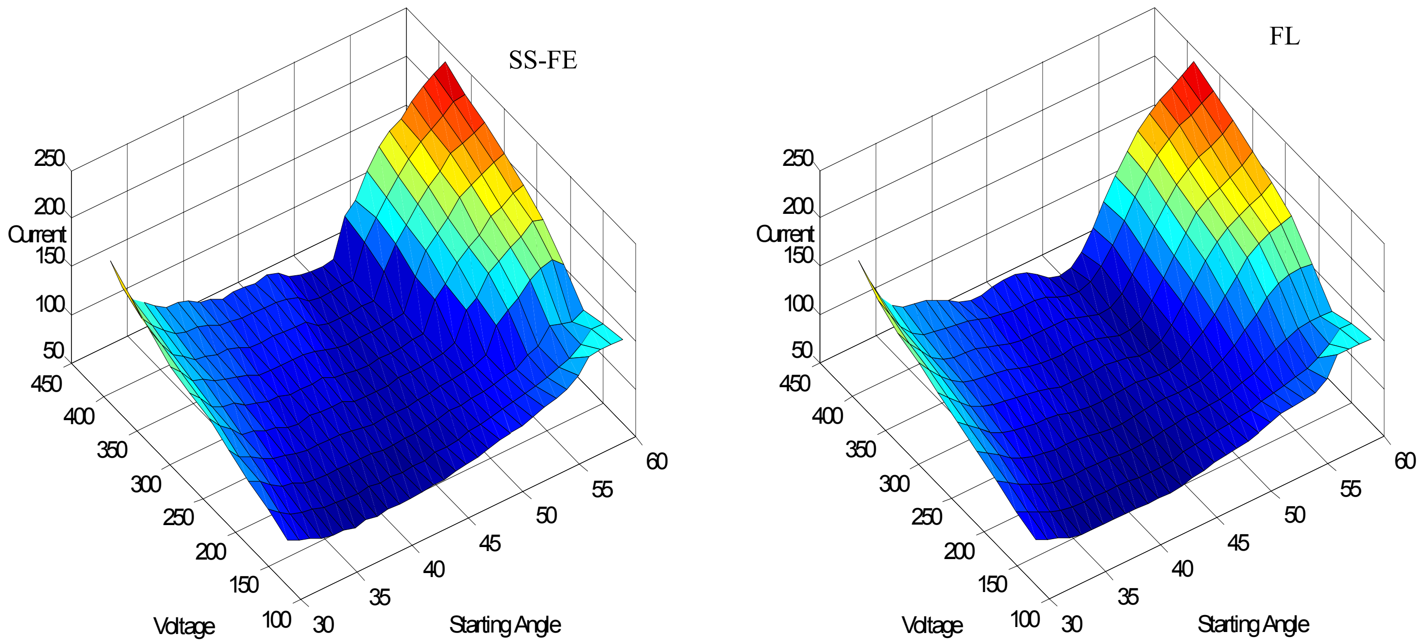
Speed Generated from the FE-SS Model and the FE Model (Under Phase Short) at Different DC Voltage and Starting Angel (Fixed Torque Load TL = 20 ft-lb)

Result Analysis (continued)



Healthy Current Generated from the FE-SS Model and the FE Model (Under Phase Short) at Different DC Voltage and Starting Angel (Fixed Torque Load TL = 20 ft-lb)

Result Analysis (continued)



Short Current Generated from the FE-SS Model and the FE Model (Under Phase Short) at Different DC Voltage and Starting Angel (Fixed Torque Load TL = 20 ft-lb)

Computing Time comparison

	Data Collection Time	Training Time	Time to Generate 100 Data Points	Total Time to Generate 100 Data Points	Total Time to Generate 1000 Data Points
Multi-Curve Model	0 min	0 min	8hrs 20min	8hrs 20min	83hrs20
AI Model (FL)	58hrs20 min	9 min	< 1 sec (Say 1sec)	58hrs 29min1sec	58hrs29 min 10sec

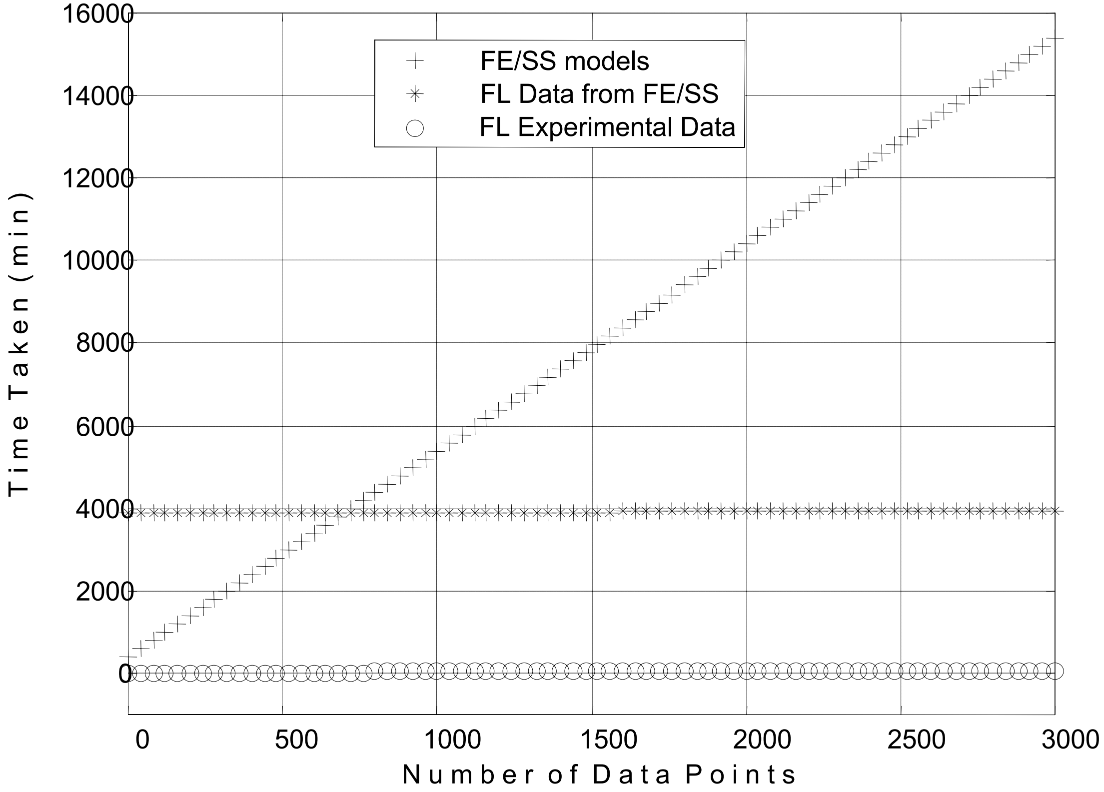
Comparison of Time Needed to Generate Data when No Experimental Data is Available.

Computing Time comparison (continued)

	Time to Create the Lookup Table	Training Time	Time to Generate 100 Data Points	Total Time to Generate 100 Data Points	Total Time to Generate 1000 Data Points
Multi-Curve Model	6hrs15 min	0 min	8hrs 20min	14hrs 35min	89hrs35
AI Model (FL)	0 min	9 min	< 1 sec	9min1sec	9min 10sec

Comparison of Time Needed to Generate Data when Experimental Data is Available for FL Model.

Time Taken by the Models to Generate Data



Comparison between the AI Models

(continued)

Data Required

Number of Data Points Needed	Normal Case	Phase Loss Case	Phase Short Case
ANN	1316 Points	1184 Points	1225 Points
FL	700 Points	650 Points	675 Points
Percentage of ANN	53.191%	54.90%	55.10%

Comparison of the Number of Data Points Needed for Training

Training Time

Training Time	Normal Case	Phase Loss Case	Phase Short Case
ANN	26 min	22min	24min
FL	9 min	7min	11min
Percentage of ANN Time	34.61%	31.81%	45.83

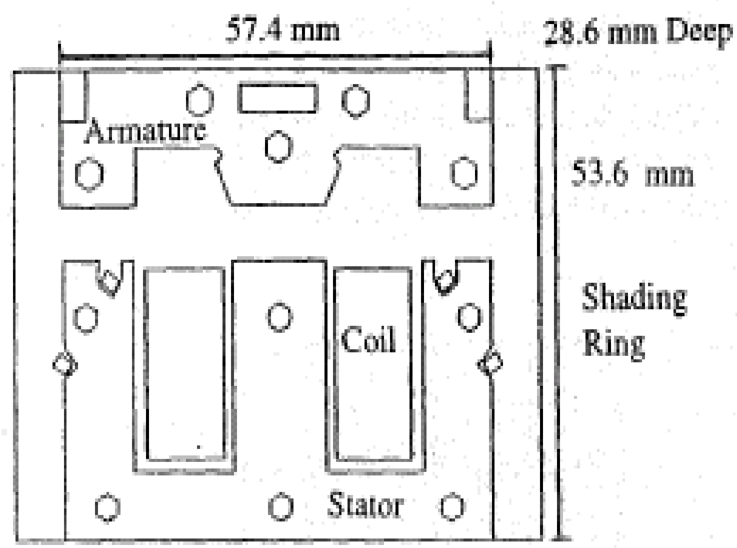
Comparison of the Time Needed for Training

Finally, it should be noted that the FL model offered accuracy as high as 97 %. Less than 3% average error was achieved in all cases and for any output. A maximum error was as low as 9% with standard deviation of no more than 2.5%.

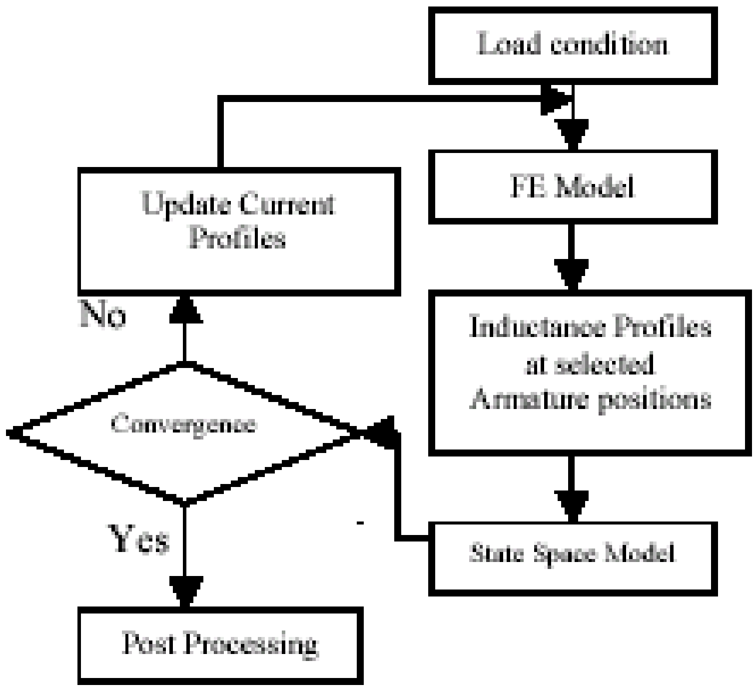
Integrated AI–EM Approach for the Characterization of AC Actuators

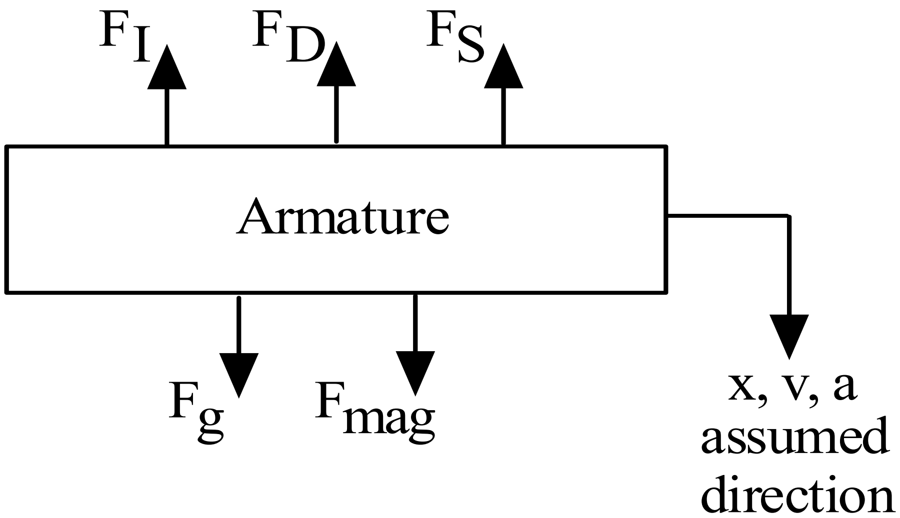
- **The performance characteristics of electromagnetic AC Actuators are predicted using an integrated Artificial Intelligence – Electromagnetic, AI - EM, approach.**
- **The approach makes use of electromagnetic field solutions in conjunction with AI fuzzy logic, FL, based models.**
- **This approach is applied to a prototype AC actuator under static and motion conditions.**
- **The results are compared to test data for verification.**

Outline of AC Actuator



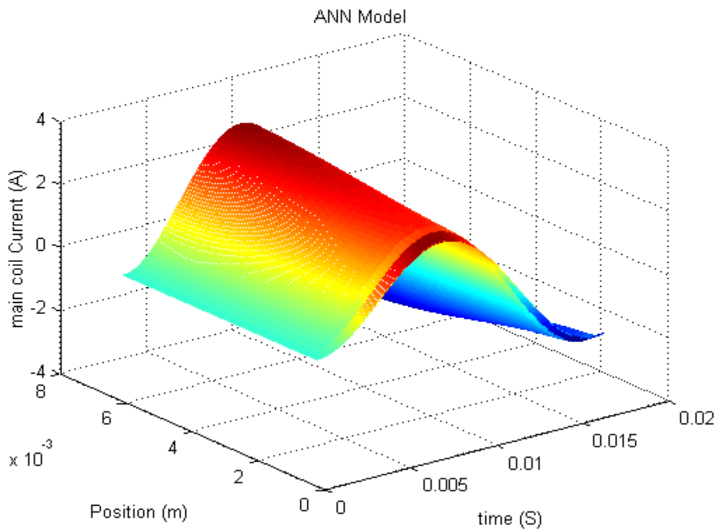
Iterative EM – SS Approach

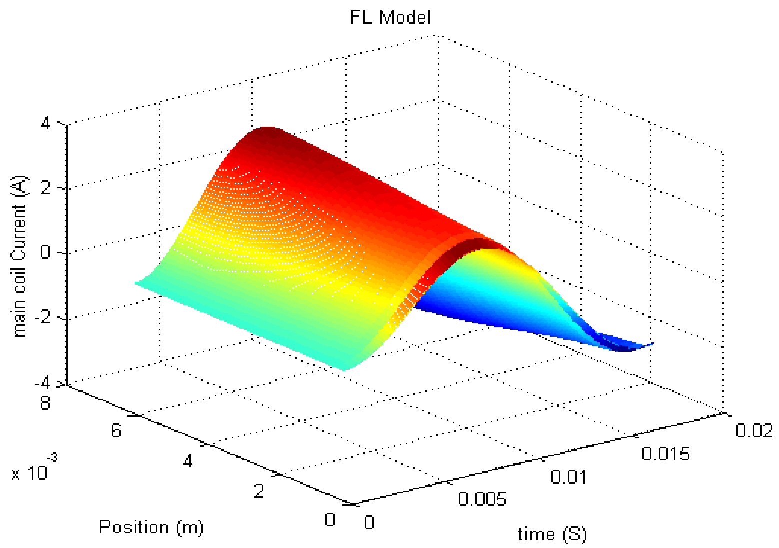




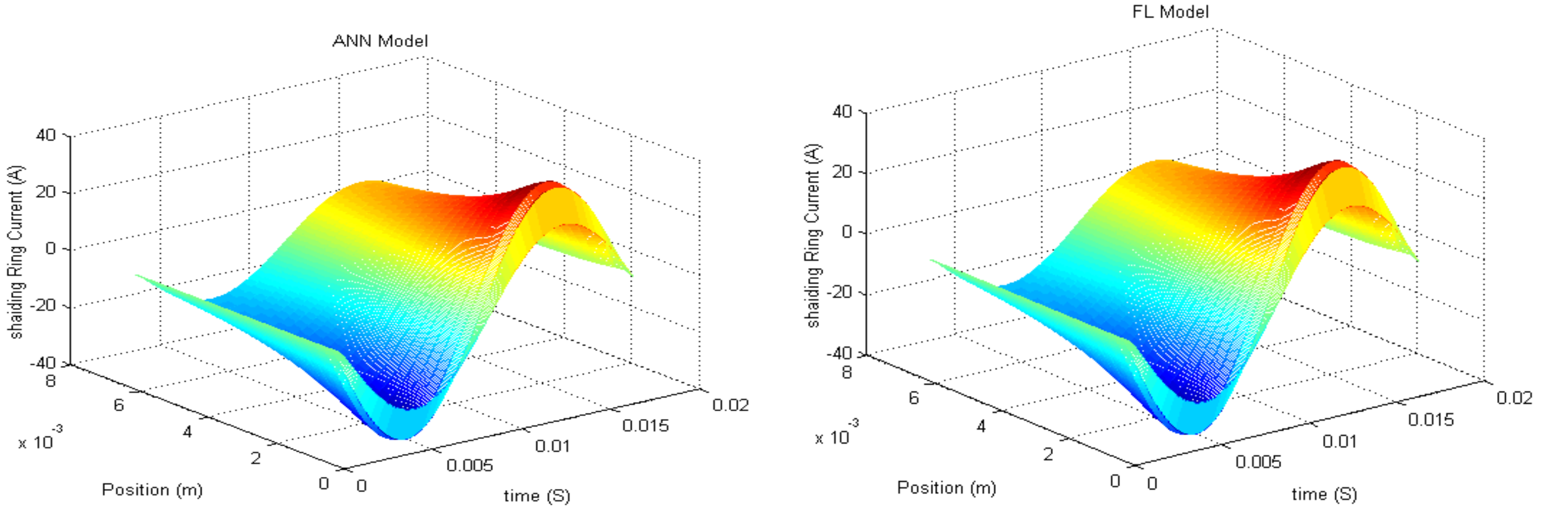
Layout of Force on Armature

- F_{mag} is the magnetic force;
- F_D is the damping force;
- g is the gravitational constant;
- m is the mass of the armature;
- K is spring stiffness, and
- x is the spring displacement
- v is the velocity



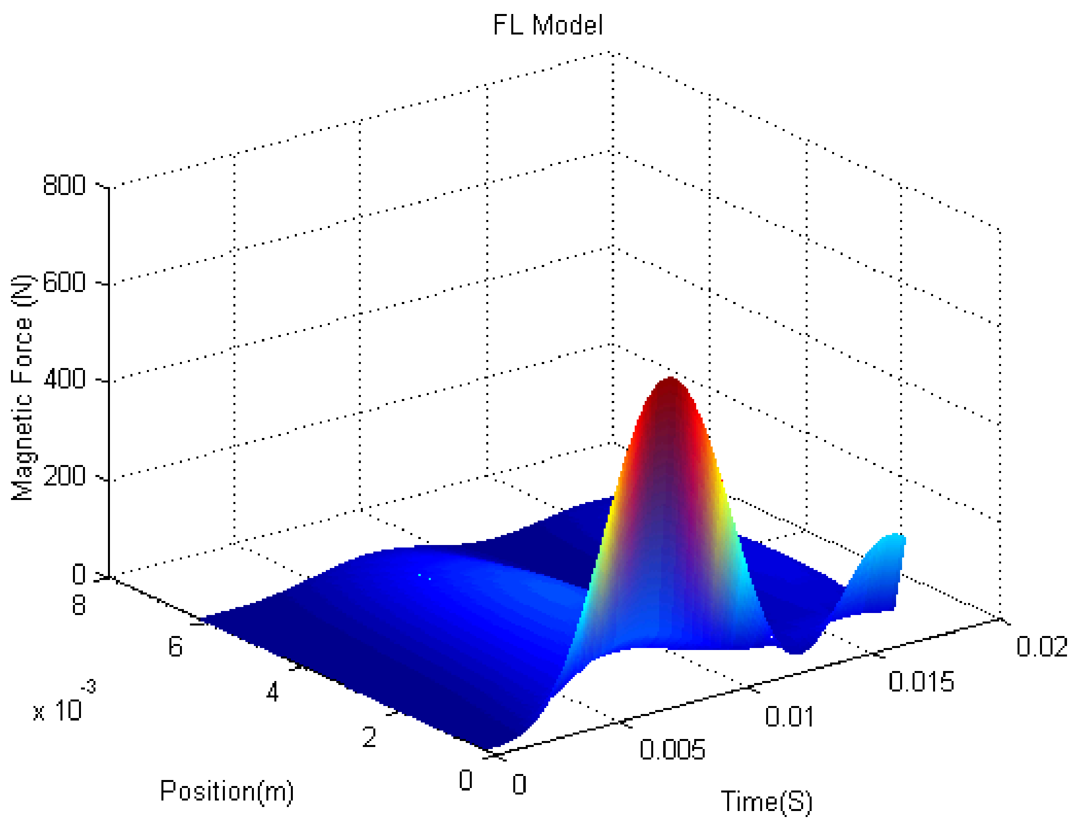


Main Coil Current vs. Time and Position

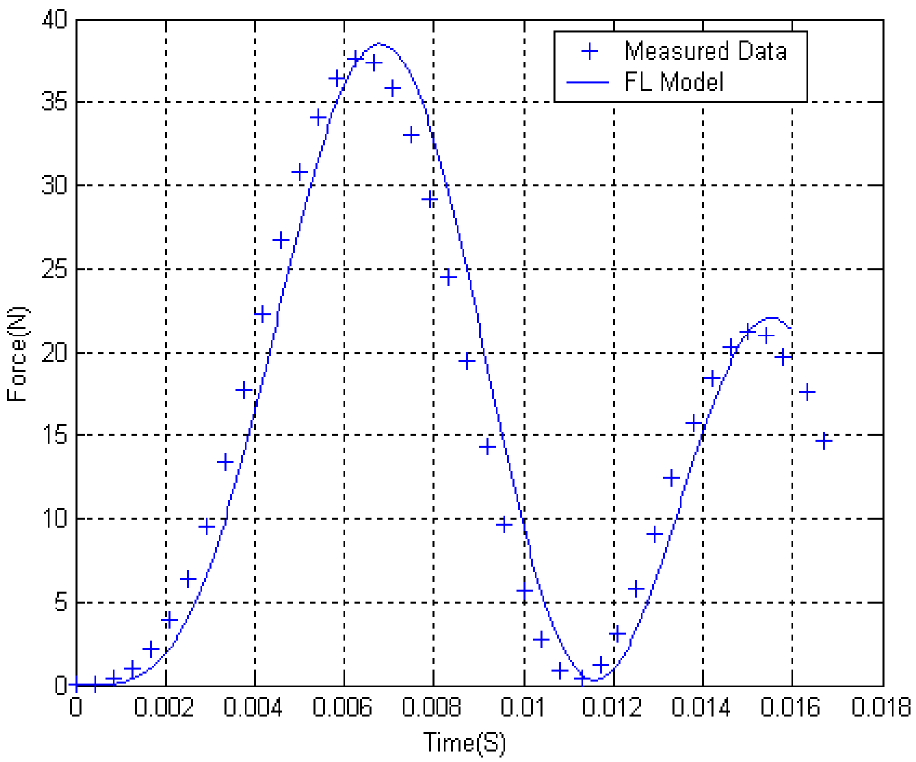


Shading Ring Current vs. Time and Position

Magnetic Force Simulation vs. Time and Armature Position at 120V RMS excitation voltage



Magnetic Force and Test Data vs. Time and at 6.096mm for 120V RMS Excitation Voltage

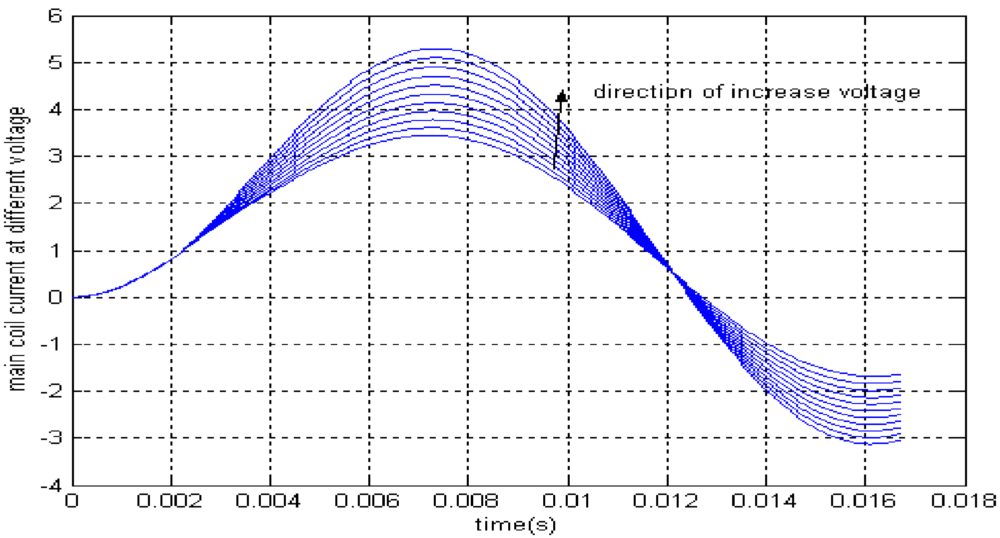


	Main Current		Shading Ring current		Magnetic Force	
	Average Error	Maximum Error	Average Error	Maximum Error	Average Error	Maximum Error
FL	0.98%	1.5%	2.027%	5.12%	1.2%	1.5%
ANN	2.10%	3.72%	3.4%	8.3%	8.2%	8.5%

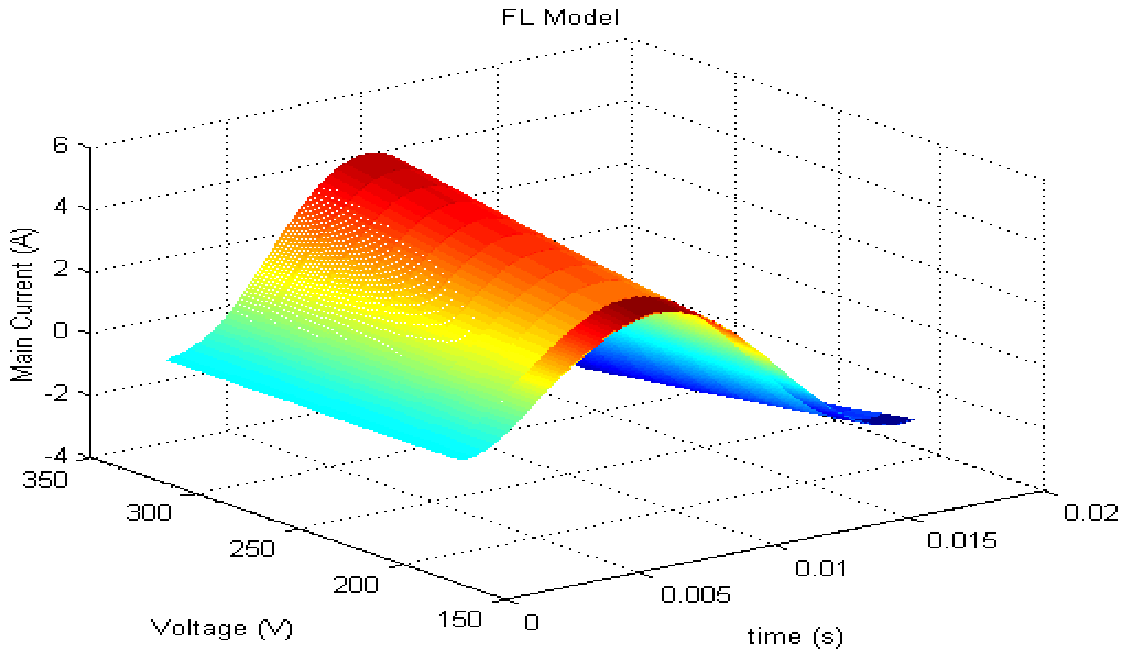
Average Error and Maximum Error for both FL and ANN relative to FE-SS Model

	Offline computation	Training Time	Online Computation for 100 data points
SS-FE	10 hrs 48 minutes	0 minutes	3 hrs 20 minutes
FL	10 hrs 48 minutes	3.5minutes	< 1 sec
ANN	10 hrs 48 minutes	27 minutes	< 1 sec

Comparison of Computational Time



Main Coil Currentvs. time for
Combined Static – Motion
Cases

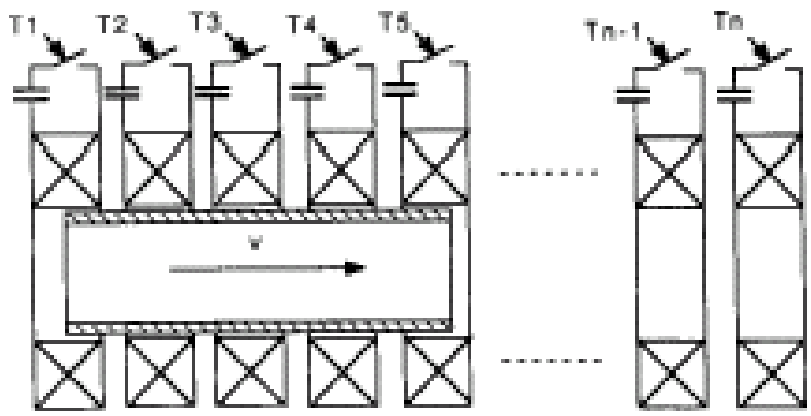


Combined Motion and Static Case Results

Motion Results are shown for 120V Case

Data	Measured	FL
Main current peak (A)	3.12	3.91
Time Ipeak (ms)	6.7	6.90
Magnetic force Peak (N)	47.10	56.77
Time Fpeak (ms)	7.56	8.40
Time to seal	16.50	14

Multistage Capacitive Driven Coil Launcher



- The stator of a launcher is made up of many stages energized according to certain time sequence.
- This time sequence is an important design parameter as it controls the acceleration of the projectile.
- To achieve maximum acceleration of the launcher; the magnetic force must be positive all the time in the desired direction. Thus the penetration depth of the flux linkage in the armature must be at a maximum level.
- The variation of the penetration depth of the flux linkage as function of the armature (projectile position) is illustrated by the magnetic field solutions shown below.